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Machine Learning Approach for Smart Distribution Transformers Load Monitoring and Management System

Jayroop Ramesh [1,*], Sakib Shahriar [1], A. R. Al-Ali [1], Ahmed Osman [2] and Mostafa F. Shaaban [2]

[1] Department of Computer Science and Engineering, American University of Sharjah, Sharjah 26666, United Arab Emirates
[2] Department of Electrical Engineering, American University of Sharjah, Sharjah 26666, United Arab Emirates
* Correspondence: b00057412@aus.edu; Tel.: +971-5-59517842

Abstract: Distribution transformers are an integral part of the power distribution system network and emerging smart grids. With the increasing dynamic service requirements of consumers, there is a higher likelihood of transformer failures due to overloading, feeder line faults, and ineffective cooling. As a consequence, their general longevity has been diminished, and the maintenance efforts of utility providers prove inadequate in efficiently monitoring and detecting transformer conditions. Existing Supervisory Control and Data Acquisition (SCADA) metering points are sparsely allocated in the network, making fault detection in feeder lines limited. To address these issues, this work proposes an IoT system for real-time distribution transformer load monitoring and anomaly detection. The monitoring system consists of a low-cost IoT gateway and sensor module which collects a three-phase load current profile, and oil levels/temperature from a distributed transformer network, specifically at the feeder side. The data are communicated through the publish/subscribe paradigm to a cloud IoT pipeline and stored in a cloud database after processing. An anomaly detection algorithm in the form of Isolation Forest is implemented to intelligently detect likely faults within a time window of 24 h prior. A mobile application was implemented to interact with the cloud database, visualize the real-time conditions of the transformers, and track them geographically. The proposed work can therefore reduce transformer maintenance costs with real-time monitoring and facilitate predictive fault analysis.

Keywords: Internet of Things; big data; cloud computing; smart grid; load monitoring; deep learning; anomaly detection

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1. Introduction

Transformers form the fundamental elements for power distribution networks. Their primary function is to distribute electric power to the low-voltage consumers side from the generating power stations through a conducting system of transmission feeders. Feeders are designed based on the current carrying capacity and the respective voltage drop required by the transformers. This constitutes the main feeder and many secondary feeders which connect commercial enterprises or domestic communities with the central power grid. Their operational ability is specified by rating condition, which guarantees a long service life of typically 20–25 years [1]. With the increasing need for energy requirements from consumers driven by the rise of technological advancements, their lifespan is significantly diminished. Overloading, overheating and feeder line faults are the major causes of failures. Its operational condition determines the availability of electricity to entire areas and is imperative to effectively manage the components of the distribution grid to mitigate the disruption of services.

Utility providers in many countries have attempted to address these prevalent problems by using the Supervisory Control and Data Acquisition (SCADA) [2]. SCADA is a computer system that detects data on temperature, voltage, power, and current. While this system reduces the frequent need to send utility personnel for site visits by providing access to data, it has certain limitations. It cannot acquire transformer health data such as the temperature, oil level, or load status of each feeder. If there is any power outage at a single feeder, the utility providers will only be alerted by customer complaints or during a maintenance inspection. Peharda et al. [2] introduce a technique that incorporates data available from SCADA systems to schedule maintenance to circumvent the lack of real-time transformer condition access. By using winding temperatures, the relative aging rate was calculated, and with active power, the working hours were estimated. There is an evident requirement for smart and reliable solutions to reduce the cost of manual labor, improve transformer monitoring and identify failing equipment in time to maintain the continuity of the power grid functionalities [3].

The emergence of technologies such as cloud computing and the Internet of Things (IoT) introduces opportunities to efficiently solve these problems. They aid the conception of smart cities by facilitating advancements such as smart homes [4], smart transportation [5], smart cafes [6], smart healthcare [7], and smart grids [8]. As reported in [9], the aging assets of the power distribution network reveal the need for intelligent, secure data collection devices, with efficient frameworks to handle huge volumes of data for real-time fault detection and predictive maintenance. The rise of machine learning and deep learning success in multiple practical domains has motivated researchers to explore its applicability in time-series problems. In particular, recurrent neural networks and long short-term memory networks have the capability to model temporal dependencies. However, addressing complex patterns of seasonality and trend remains an open problem.

There is a need for scalable time-series anomaly detection from long-term IoT data to enable predictive maintenance and effective monitoring. As such, the feasibility of multiple machine learning and deep learning methods for anomaly detection using real-time data is studied and reported as well.

The proposed work presents the following contributions:

- An enhanced real-time distribution transformer monitoring system leveraging a low-cost IoT gateway and sensor set the module to collect the three-phase load current profile, temperature, and oil level.
- An exhaustive comparison of different anomaly detection algorithms for automated fault diagnosis.
- The system uses cloud and Big Data principles to achieve scalability and security and enable further intelligent analytics for optimizing energy consumption profiles.
- The real-time information including geographical location markers is communicated to utility providers through a mobile application, and additionally, it sends alerts in the case of faults.

This paper is organized as follows: Section 2 provides the core terminologies, Section 3 provides a review of recent literature, Section 4 outlines the design requirements, Section 5 explores the proposed architecture, Section 6 presents the implementation, Section 7 puts forth the machine learning components, Section 8 presents the results, Section 9 carries out a discussion, and Section 10 concludes the work.

2. Background

An anomaly is defined as an observation at a point in the time series that differs significantly from the previous observations. A sequence is basically: $x_{t-w}, x_{t-w+1}, \cdots, x_{t-1}, x_t$, where t is the current time, and w is the window of interest. Consider this sequence as a series of values from a single measuring source, i.e., an oil temperature sensor. This follows a certain distribution, Gaussian or otherwise, denoted by $p(x)$. Suppose a new value x_i is recorded, such that $p(x_i) < r$, where r is a dynamic threshold reflecting the cumulative contributions of the preceding data values; then, it shows a potential anomaly [10].

Generally, anomaly detection has two primary approaches. Representation learning is when the goal is to learn the overall distribution of the time-series data so anomalous points are rendered obvious. Due to complex seasonality, trend, and noise saturation, it is recommended to transform raw time series into feature spaces where the context is simplified. For instance, anomalies are easier to detect in time series with these aforementioned components removed. This is employed in recent works with deep learning such as [11,12]. Fault detection involves the selection of an empirical threshold for the learned representation based on statistical tests such as the 3-sigma rule. However, static thresholds might be insufficient if the data are complex and clear thresholds are not known for the domain. This is common when standard machine learning is used as in [13,14].

While many works in the literature have addressed pervasive issues in a satisfactory way, there remain considerable limitations. They are isolated systems and are constrained to operate within their testing environment only. Real-time data are collected but communicated to relevant stakeholders only in the case of faults. This hinders the efficiency of monitoring and therefore affects the reliability of the system. Additionally, the implementations were deployed on customs servers, privacy and security are another concern. Recently, Gupta et al. [15] presented an efficient home energy management and analytics system that utilizes smart meter data together with Big Data processing paradigms to provide a granular perspective on real-time consumption. The unified platform was scalable and allowed monitoring home energy consumption from both utility and consumer levels. The multi-faceted nature of such solutions in similar contexts motivates the research employed in this work. Anomaly detection with time series is challenging because of intricate temporal dependencies, abrupt fluctuations in trend and seasonality, and the limited availability of labeled anomaly datasets. If there are unlabeled anomalies in the underlying distribution, the model will learn them along with the normal data, leading to problematic performance during implementation. Noticeably, this is not resolved in the context of distribution transformers.

The proposed system adopts the advantages of the cloud, automated learning, and Big Data processing pipelines to be expandable, scalable, and secure while addressing the limitations of the current literature.

3. Related Work

This section outlines related existing work for energy management systems at the larger level as well as transformer monitoring pertaining to the context of our work.

Many developments were observed in the Energy Management System (EMS) area, especially applied to housing [16], commercial [17], and manufacturing sectors for power management and minimizing energy utilization. Anomaly detection approaches that extend the features of IoT elements that are already part of EMS can create more value by using much of the shared system infrastructure. Ref. [16] set up an IoT-based energy management system for smart homes where energy consumption data are acquired from smart homes with a System on Chip (SOC) and communicated to stakeholders. Ref. [17] proposed a general blueprint for an IoT-based energy management system that measures levels of current, voltage and derived power using sensors interfaced with Arduino UNO. SMS alerts are sent based on thresholds via a GSM-enabled network to users.

Machine learning is increasingly being applied for load forecasting, where it is employed oriented toward residential community or commercial entity levels for peak demand predictions and power planning [18]. The authors in [19] propose an IoT dashboard for visualizing the readings of voltage, current, real power, reactive power, apparent power, power factor, and energy consumption, with a Gaussian support vector machine regression for forecasting energy consumption using the historical monthly reported readings of the same variable along with recorded weather conditions.

The works in [19–21] in particular purport that anomaly detection is a worthwhile addition for future studies, which can build on top of existing IoT and ML systems.

Wornpuen et al. [22] introduce one of the first transformer monitoring systems in the literature. They separated their transformer measuring units into small groups of clients and designated a central master. The clients measure voltage, current, power, and temperature, and they communicate with the master using radio frequency at the 433 MHz bands. The master unit has a Global Service Mobile (GSM) modem and transmits all data from itself and the client to a remote database server.

The authors in [23] expand the scope using IoT, and they additionally consider oil sensors, vibration sensors, and humidity sensors in their work. They use a PIC microcontroller to interface with the sensors and a GPRS module to send the collected values to an online interface for utility engineers. However, their system is only active for any emergency conditions and does not provide real-time monitoring capabilities.

A real-time transformer health monitoring system was proposed by [24]. The system uses a short message service (SMS) to obtain any abnormality information about the systems to designated mobile phones. The proposed GSM-based system also integrates a PIC microcontroller and sensors to monitor load currents, over-voltage, transformer oil level, and oil temperature.

The work in [25] developed a transformer monitoring system for detecting health based on the parameters of voltage, current, and temperature. The sensors were connected to a PIC microcontroller, which sent data through a GSM-enabled network to a server.

The researchers in [26] outline another IoT transformer system that monitors faults by using current, voltage, temperature, and humidity data. They implemented a prototype with the NodeMCU microcontroller and interfaced it with sensors, relays, buzzers, and LEDs. The readings were forwarded to an online web portal which could be monitored by relevant stakeholders. The overloading of distribution transformers can have significant consequences on power distribution.

To mitigate this, an-IoT based thermal monitoring and protection system was proposed by [27]. A node MCU microcontroller is utilized to interface with temperature, humidity, and current sensors. A DC fan was also integrated to provide a cooling mechanism in overheating scenarios. To avoid complete termination and load-shedding, a three-phase logical tripping mechanism was introduced. The proposed system was cost-effective, but the authors reported some delays during the testing phase.

Nelson et al. [28] proposed a remote monitoring system to observe the conditions of distribution transformers. In addition to the temperature and oil level monitoring using sensors, the authors also utilize an energy meter to track transformer loading and a microphone to monitor humming noise. The sensors were interfaced with a PIC microcontroller to provide real-time monitoring. A health index was also proposed to describe the transformer's health status based on the four measures.

The authors in [29] propose an IoT-based real-time monitoring and maintenance of distribution transformers. Voltage, load current, temperature, and oil level were measured by interfacing with the ATMEGA328 microcontroller. By Messaging Queuing Telemetry Transport (MQTT) instead of HTTP, the proposed system was energy-efficient and provided better response time. Despite the numerous contributions in the literature in the context of real-time monitoring of transformers, automatic fault and anomaly detection remains a challenge.

The existing works in transformer monitoring are summarized in Table 1. Therefore, in this work, we leverage machine learning and IoT to provide real-time monitoring and anomaly detection for transformers. The proposed research is dealing with the last mile within the power distribution system. Most of the reported literature shows the performance on the higher-voltage side, where the utility monitoring system can only show the load of the whole transformer. Our work is completed on the lower-voltage side of the transformer where the utility personnel can monitor the performance of each feeder of the transformer remotely using a mobile application or web dashboard. Such a system allows the utility to isolate any failure at the granular feeder level (low-voltage) rather than at a whole transformer level (high-voltage).

Table 1. Summary of recent literature focusing on smart transformer monitoring and management.

Source	Application	Implementation	Limitations
[22]	Transformer monitoring	Measure voltage, current, power, and temperature. Communicates with a GSM modem to a remote database server.	Does not utilize IoT and machine learning.
[23]	Transformer monitoring using IoT	PIC microcontroller to interface with the sensors and a GPRS module to transmit the readings.	Does not provide real-time monitoring.
[24]	Transformer health monitoring	GSM-based system integrated with PIC microcontroller to monitor load currents, over voltage, transformer oil level and oil temperature	The system was not tested in operational scenarios and does not utilize machine learning for fault detection.
[25]	Transformer health monitoring using IoT	Observes temperature, voltage, and current of the transformer. PIC microcontroller to interface with sensors and data sent through GSM-enabled network.	Does not utilize machine learning for fault detection.
[26]	IoT-based transformer monitoring and protection	Monitors current, voltage, temperature, and humidity data. The sensors were interfaced with NodeMCU microcontroller. Buzzers, LEDs, and web application provide cost-effective, user-friendly, and remote monitoring.	Does not utilize machine learning for fault detection.
[27]	Thermal monitoring and protection system for transformers using IoT	Node MCU microcontroller was used to interface temperature, humidity, and current sensor. Cooling system and tripping mechanism were introduced.	Reported delays during testing and does not utilize machine learning for fault detection.
[28]	Remote monitoring system for transformers	PIC microcontroller was used to interface temperature and oil level sensors. Energy meter provided transformer loading information and a microphone was used to measure humming noise.	The system was not tested in operational scenarios and does not utilize machine learning for fault detection.
[29]	IoT-based real-time monitoring and maintenance of distribution transformers	Monitors voltage, load current, temperature, and oil level by interfacing sensors to ATMEGA328 microcontroller. The system uses MQTT for energy-efficient and faster communication.	The system was not tested in operational scenarios and does not utilize machine learning for fault detection.

4. Design Requirements

4.1. Design Considerations

The objective of the proposed IoT-based transformer monitoring system is to acquire operational and environmental parameters and transmit this to a client application in real time. The system is deployed in a feeder network as shown in Figure 1.

Each node is indicated by one, two, three, four and five are buses. The primary feeder has a three-phase current I_{12} which originates from the step-down transformer and diverges into specific sub-feeders based on the network configuration. Each of the four loads is a small community of houses ($n = 5$), which consumes a certain level of power from the primary feeder. The intermediary three-phase currents of I_{23}, I_{34}, and I_{25} facilitate interconnection between the primary feeder and the loads. By focusing on monitoring each available feeder available to a primary feeder, faults can be detected at a granular level, thus improving the reliability and stability of the distribution network. Finally, the data associated with temperature and oil levels are also collected, thereby adding to the holistic nature of the proposed solution.

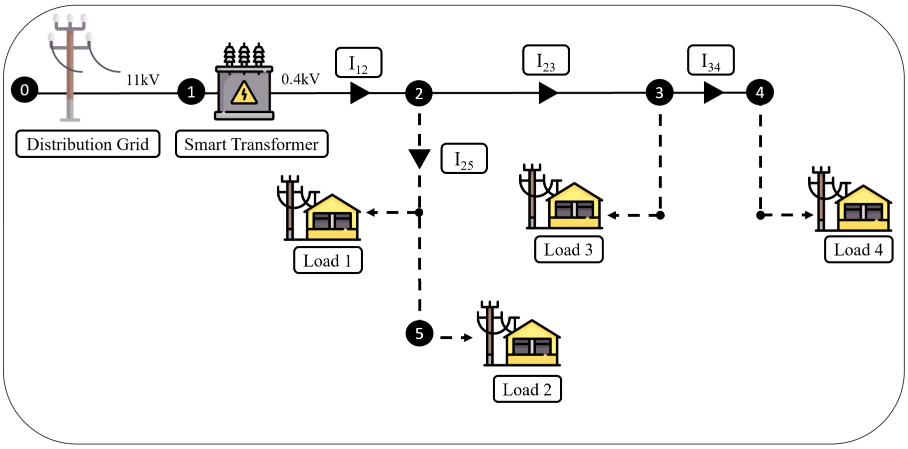

Figure 1. Feeder network system for one area.

4.2. Functional Requirements

The proposed functional requirements describe the expected behavior of the system.

- The system authorizes utility providers to sign in with their credentials.
- The system allows authorized users to register multiple monitoring devices.
- The system should be able to monitor transformers parameters of three-phase current across all feeders, temperature, and oil levels.
- The system allows authorized users to change the monitoring frequency of these parameters.
- The system allows authorized users to change the threshold conditions for detecting anomalies remotely.
- The system makes available the collected data in real time to users through a cloud-hosted mobile application.
- The system lists all registered monitoring devices and the ability to view individual data across any time period.
- The system generates maps and displays to users the geographical locations of each monitoring node in real time.
- The system generates alerts in the case of any detected fault and notifies the user through the mobile application.
- The system visualizes the status of the transformers by changing the colors of the location markers on the maps.
- The system displays graphs to visualize the data acquired from each transformer in real time.

4.3. Non-Functional Requirements

The proposed non-functional requirements describe the performance and reliability needs of the system.

- The system must be capable of real-time operations with a maximum latency of 20 s.
- The system must be efficient in terms of energy consumption and utilize minimal power during operation.
- The system must be secure and private such that unauthorized access is not possible.
- The system should maintain local backups in the event of connection failures.
- The system should be able to scale with additional devices without affecting the robustness of the existing infrastructure.
- The system must be manageable remotely and obscure complexity through a user-friendly interface for users.

5. Proposed Architecture

The proposed system in this work follows the three-tier architecture for purposes of modularity, scalability, and testing. The complete architecture is presented in Figure 2.

The monitoring modules constitute the data acquisition layer. The cloud and Big Data services constitute the cloud processing layer. A cross-platform mobile application constitutes the application layer. Each zone consists of the primary feeder and sub-feeder network discussed in the Design Requirements section. The monitoring module in a zone communicates with a central master monitoring module, which then propagates the collected data to a Big Data processing cloud platform. The mobile application interfaces with the stored data on the cloud and retrieves the monitoring status in real time. Alerts are also generated in the event of abnormalities, and the conditions will be discussed further in the next section.

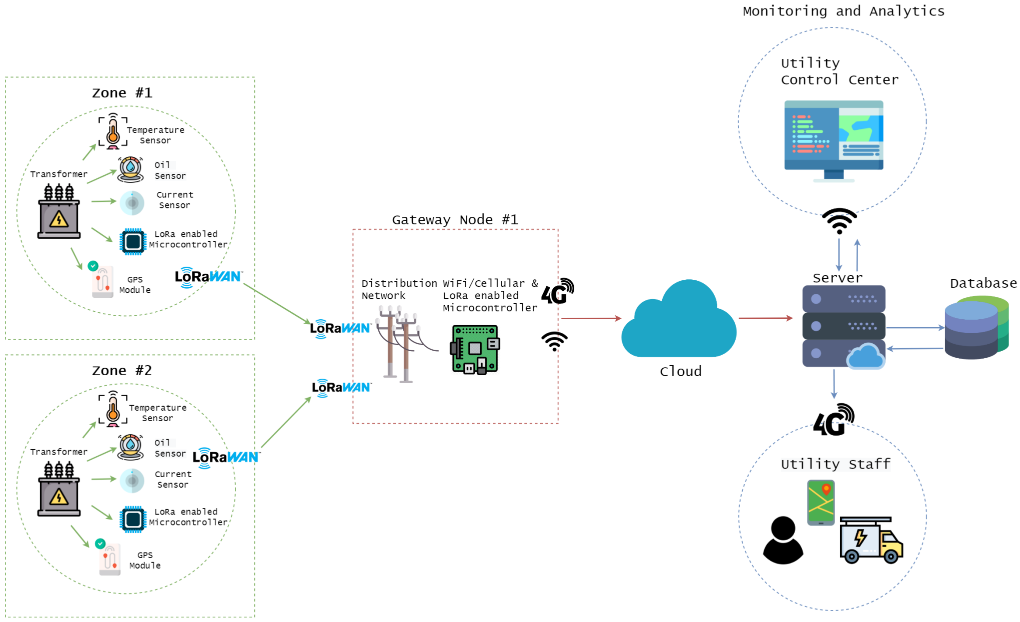

Figure 2. Proposed architecture.

5.1. Data Acquisition Layer

The distribution transformer type monitored in this work is a three-phase transformer, with a power rating of 1500 kVA, and steps down the voltage from 11 to 0.4 kV. In this layer, there are two types of modules. There is the monitoring module deployed at each main feeder, and there is a central gateway at a convenient location that provides internet connectivity to the other modules. The monitoring module is separated from the gateway module to reduce the overall cost of components and avoid the usage of excess power needed to maintain connectivity with the cloud.

The monitoring module comprises of the Raspberry single board microcontroller (RPi) [30], three-phase current sensors, temperature, oil level sensors, and GPS components with relays. The sensors are interfaced to the RPi ports using the relays and communicate using the inter-integrated circuit communication protocol (I2C). Digital signal conditioning onboard the RPi is used to filter out undesired frequency and scale sensor values to the required measurement range. This module is enabled with a communication protocol called Long-Range Wide-Area Network (LoRa), which is a robust technology that offers relatively better performance in challenging resource-constrained environments [31].

The gateway is another RPi but with LoRa, Wi-Fi/Cellular, and MQTT communication capability. Message Queuing Telemetry Transport (MQTT) uses the publish/subscribe model and is preferred for bandwidth-limited networks and allows edge devices to push data directly to a cloud MQTT broker [31]. The gateway is initially registered on the cloud services and subsequently establishes connections with the cloud processing layer and publishes data at a user-configurable frequency. The RPi was selected against alternatives such as Arduino, due to better I/O availability, memory, and computing performance.

5.2. Cloud Processing Layer

This layer utilizes the services of IoT Core, Pub/Sub, Cloud Functions, and Firestore Database provided by the Google Cloud Platform to create the Big Data processing and storage pipeline [32]. These components realize the Big Data architectural principles of data ingestion, aggregation, storage, and analytics [33].

IoT Core is a cloud-managed service allowing users to securely connect and ingest data from distributed IoT devices. It consists of a device manager to register devices for remote monitoring, and an MQTT protocol bridge which is used by the central gateway to connect to the cloud platform. It also handles authentication and serves as the MQTT broker for the communicating devices.

Pub/Sub is an asynchronous messaging service for event-driven applications and is forwarded telemetry data in the form of messages from monitored transformers. These messages are published to a topic in key-value formats, where paths are defined such as *{topic_transformer_id_feeder_number_current_phaseA}* or *{topic_transformer_id_temperature}*. Clients, such as the database, subscribe to these topics and are updated in real time as the values of the transformer change. Cloud Functions facilitate the configuration of automatic code triggers based on certain conditions. They are deployed as serverless functions and therefore are scalable for real-time data processing. In this work, triggers are constructed for new data and different detected anomalies. New data are appended to the database, while alerts are sent to users in the case the sensor values violate certain conditions.

Firestore is a NoSQL cloud-hosted database that interfaces with the cloud functions to retrieve the latest transformer data and allow the user application to access the data in a controlled, uniform way.

5.3. Application Layer

The application layer is the interface with which users can view and be notified of the monitored data parameters as visualizations or historical records. The mobile application in this work is developed using the cross-platform libraries of Ionic and Angular. This allows the same application, without many changes, to be accessed on different mobile devices and web platforms. The list of transformers, their monitored parameters, and their history can be observed on the application. A user can view the geographical locations of the monitored transformers on maps. They are displayed as colored markers, where a certain color represents the current health condition of the transformer. Data are exchanged with the cloud database using the JSON format. A background service retrieves the latest updates from the database based on the triggers specified in the cloud functions.

6. IoT System Implementation

The system was tested in the University City, Sharjah, United Arab Emirates using simulations mirroring the power requirements and previous data of the locality. The simulations were generated in real time using the Power Systems Computer-Aided Design (PSCAD) software. It is assumed that there is primarily a three-phased balanced load system for these following experiments. It is worth mentioning that if the loads are unbalanced, the current of the phases will be different. Therefore, some of the database recordings were additionally modified to simulate the various scenarios that can be possible with this system as well. These values were then propagated to different modules to emulate the behavior of real transformers. Five monitoring modules were deployed with a central gateway module situated at an equidistant location from the other modules. They are assigned arbitrary IDs and Manufacturer names for this experiment. The readings were transmitted by the module at a frequency of 15 min to provide a sample test case in this section. We see that the five anomalies generated (all overloads) across a time period of 3 weeks were able to be captured. Figure 3 depicts the sequence diagram and the flow of data from the transformers to the user application.

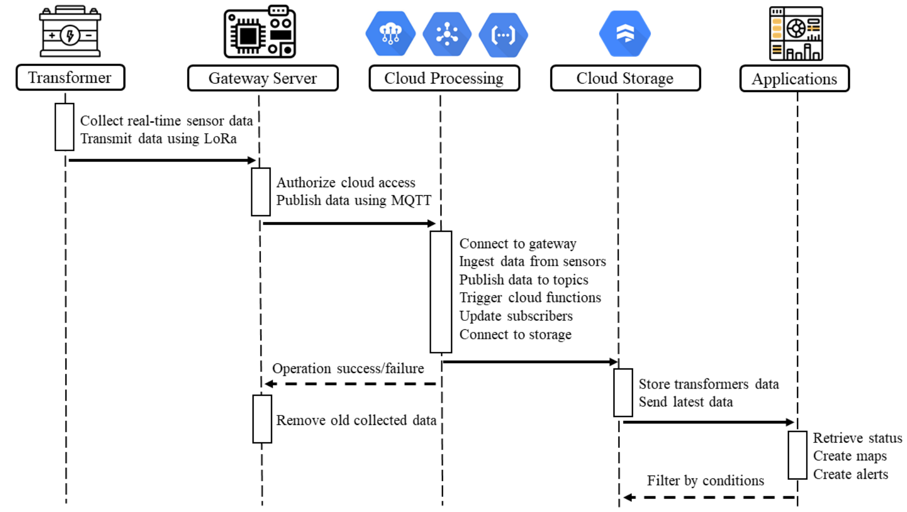

Figure 3. Sequence diagram of the system.

The data are propagated through the IoT core, to the Pub/Sub, and updated by the Cloud Functions as per the topic messages. The data are available on Firestore where the location, feeder currents, temperature, and oil level for transformer with ID = 05064 are shown in Figure 4.

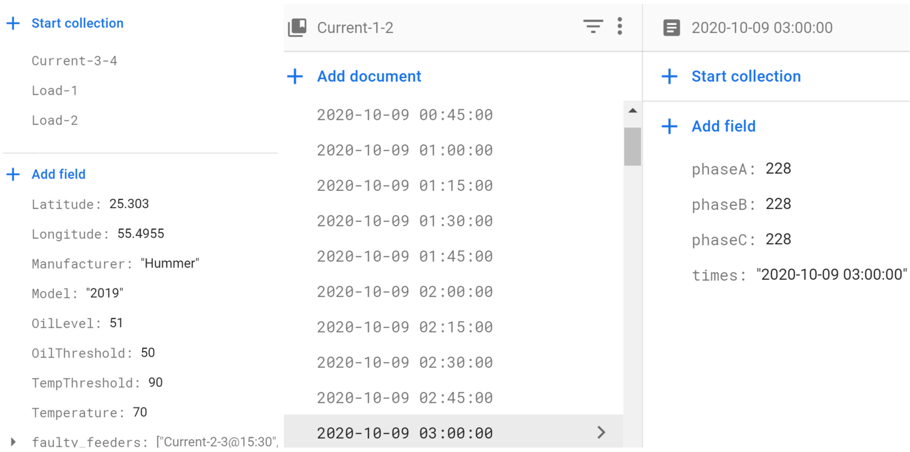

Figure 4. Transformer data available in cloud storage.

The threshold values for oil and temperature can be observed as well. The historical data obtained from the transformer are sorted in order of acquisition timestamp.

Figure 5 shows the list of monitored transformers and the historical three-phase current values accessed from Firestore by the mobile application in tabular format for granular inspection. Feeder currents for Load 1 exceed the provided threshold from 3:30 p.m. The Cloud Functions take the threshold value from the database, compare it with the current real-time value, update the application, and generate a notification alert for the user.

The orange background around the transformer metadata indicates an alert for an anomaly and redirects the user to more details. The values in green indicate current values that did not exceed a threshold for Load 1 associated with a certain oil temperature anomaly, while the values in red shows overloaded values. The mobile application is capable of querying data for any or all transformers based on certain filters, such as date, time, location and last detected faults.

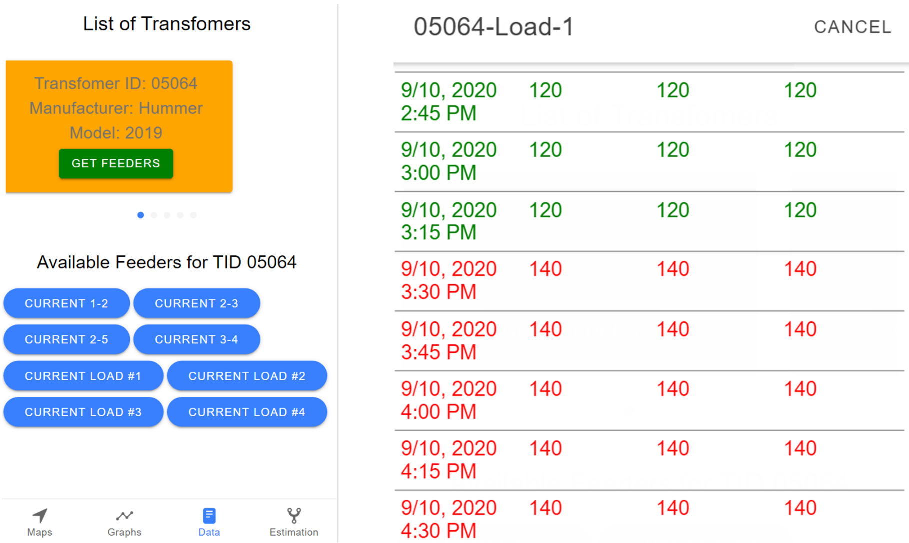

Figure 5. List of transformers and feeder current values on mobile application (green: normal, red: anomaly).

Figure 6 shows the same three-phase balanced currents in terms of their root mean square (RMS) value visualized in the form of graphs on the application with the threshold values clearly indicated for convenient visual inspection.

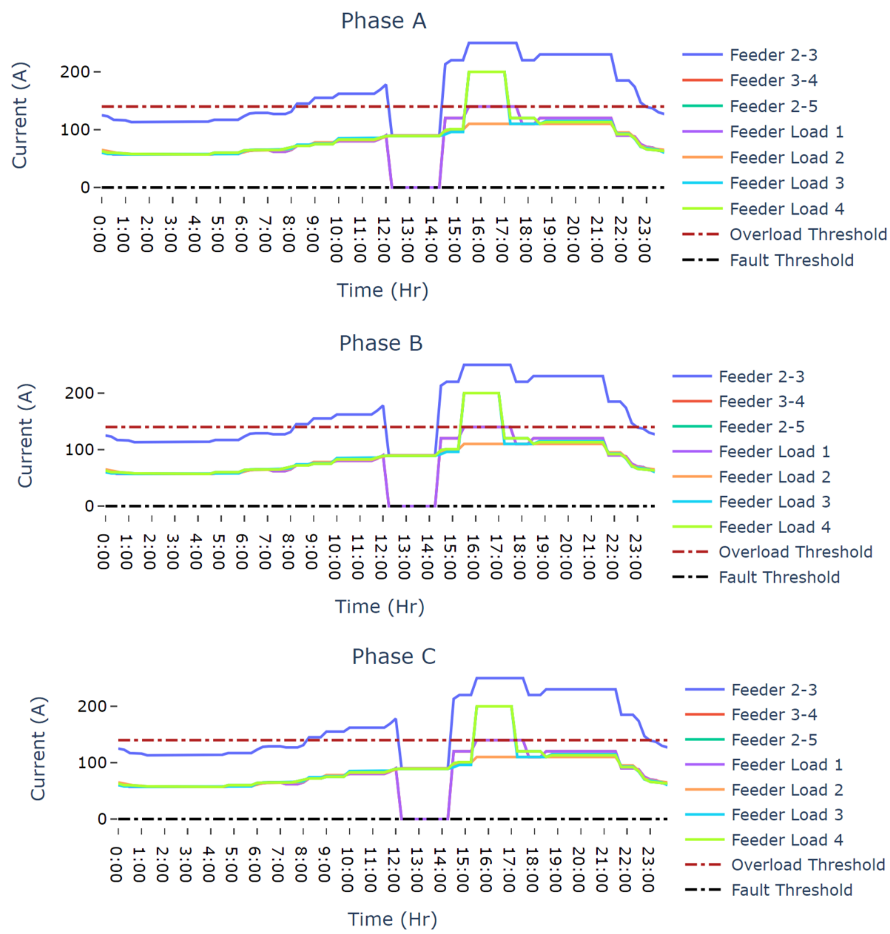

Figure 6. Graph visualizations of feeder current values on mobile application.

As can be noted, Load 1 feeder currents are crossing the upper threshold between 3:30 p.m. and 4:30 p.m. corresponding to oil temperature, which is consistent with the tabular data presented previously.

Figure 7 shows the Google maps diagrams available on the mobile application for the user to ascertain the geographical location of the transformers.

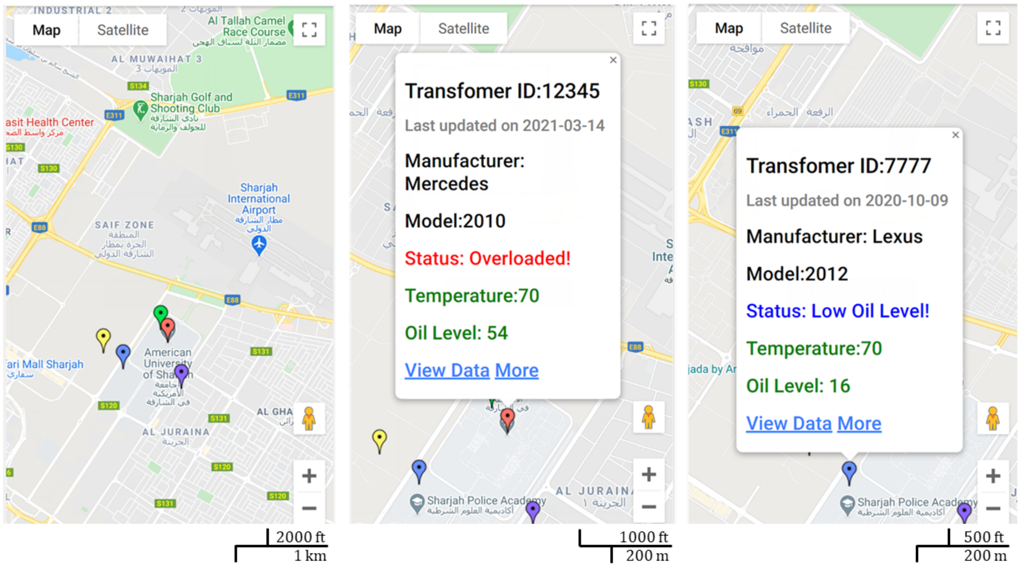

Figure 7. Map markers indicating status on mobile application.

The marker colors correspond to the following conditions and criteria. Other than the operating condition, the other four states each have a certain type of fault.

1. Green: Operating (No Anomaly)
2. Red: Overload (Anomalous value (predicted) is high)
3. Purple: Down (Anomalous value (predicted) is low)
4. Yellow: Overheat (Temperature > 90 °C)
5. Blue: Malfunction (At least one current sensor is not recorded for 24 h)

When any of the conditions are met, the markers change color to represent the particular state of the transformer. In the event of multiple detected problems, the marker changes color to the most recent condition that the transformer values have satisfied. For instance, when a transformer's condition is within the normal operation, the marker is green. If overheating (yellow) followed by an overload (red) is detected, the mobile application sends two separate alerts but only indicates the overload (red) color on the map.

7. Analysis Layer

To facilitate anomaly detection pertaining to the behavior of the transformers, a historical dataset consisting of readings from similar transformers sharing load capacity, manufactured age, measuring units, and installed environment conditions is considered [34]. The dataset is sourced from a private company, KernelSphere Technologies, in the state of Tripura, India. Much like the system proposed in this work, there is a consistency between the dataset and the small volume readings acquired, where the summer months have consistent behavior, but the winter months appear to have decreased power usage. It is suspected that the presence of external factors, such as mild winter climates, and alternative heating sources lead to this lower power usage.

7.1. Dataset

These data are originally collected via IoT meters placed on the distribution transformers from 25 June 2019 to 14 April 2020 with a sampling frequency of 15 min. The parameters measured or derived by the IoT devices were three-phase current (A), three-phase voltage

(V), active power (kW), reactive power (kVar), and apparent power (kVA). Additionally, the operational state of the transformers was also collected in terms of the ambient temperature indicator (ATI), oil temperature indicator (OTI), and winding temperature indicator (WTI). The OTI is connected to an alarm which in turn is connected to an oil temperature trip (OTT). The OTT shuts off the electrical flow to the transformer to prevent further overheating and potential equipment damage, and this is flagged as an anomaly [34]. After applying Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) hypothesis testing and yielding a p-value < 0.05, the time-series readings of three-phase current (IL1, IL2, IL3) and oil temperatures (OTI) are seen to be stationary. Transformer faults arise when the three-line currents in the secondary become unequal due to an increase in oil temperature and an unequal potential drop in the three lines. Line currents are positively correlated with the oil temperature linearly and positively, as per Pearson correlation. However, if there is a non-linear reason for this owing to external factors, then linear methods fail to capture this relationship. Therefore, we also utilize deep learning methods in addition to simpler methods.

After filtering missing data, the updated dataset consisted of 17,207 readings from 14 July 2019 to 14 April 2020. The training set consisted of 14,169, and the testing set consisted of 3471 contiguous data readings. From both subsets, there are only 33 anomalous readings in total.

7.2. Algorithms

The algorithms used in this work are selected with the rationale of inherently finding anomalous patterns and/or capturing the general behavior of the normal data values. This is intended to remove intermediary steps and introduce robustness for periodicity, trend, and similar characteristics.

7.2.1. Isolation Forest

Isolation Forests (IF) are ensembles of binary decision trees generated for random sub-samples from the dataset, wherein each tree in the ensemble is an Isolation Tree, and anomalies are classified as instances that have short average path lengths on the Isolation Trees. The methodology of the algorithm explicitly isolates anomalies rather than profiling normal instances by leveraging two quantitative properties. First is that the anomalous readings are far fewer in comparison, and their attribute values diverge from those of normal instances. The anomaly score for decision making is defined in Equation (1). Therefore, “few” and “different” points from the dataset are isolated and tend to be situated near the root of the tree, whereas normal points cluster toward the deeper end of the tree [14].

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{1}$$

where $h(x)$ is the path length of an instance x, $c(n)$ is the average path length given, and n is the number of nodes.

7.2.2. One-Class Support Vector Machines

One-Class Support Vector Machines (SVM) essentially capture the regions in a higher-dimensional feature space where the probability density of the normal data is most distributed marking a spherical boundary, and the anomalies lie outside this margin. The volume of this hypersphere is minimized to tune the incorporation of outliers.

7.2.3. Recurrent Neural Networks

Recurrent neural networks (RNN) are generally applied to sequential and time-series data, owing to their capability of processing short-term dependencies. To address the limitations of vanishing gradients and capture long-term dependencies, long short-term memory (LSTM) network variants are considered. The gated recurrent unit (GRU) is yet another variant of RNN with fewer internal components than LSTM. LSTM fares better in accuracy when large, complex datasets are involved, while GRU converges similarly with less memory consumption and faster speeds on smaller datasets. In this work, networks using both variants are tested. LSTM networks foundationally contain three components or activation gates responsible for providing memory to the network and controlling the flow of information. These gates are the input gate i_t, the forget gate f_t, and the output gate o_t, as defined in Equation (2):

$$\begin{aligned} i_t &= \sigma(w_i[x_t, h_{t-1}] + b_i) \\ f_t &= \sigma\Big(w_f[x_t, h_{t-1}] + b_f\Big) \\ o_t &= \sigma(w_o[x_t, h_{t-1}] + b_o) \end{aligned} \tag{2}$$

where σ represents the sigmoid activation, w_g represents the weights for the corresponding gates, x_t represents the input values at the current timestep, $h_{(t-1)}$ represents inputs from the previous LSTM block, and b_g represents bias values for corresponding gates.

7.2.4. Auto-Encoders

Auto-encoders (AE) condense the sensor measurements into an embedding or low-dimensional representation which is capable of capturing the correlation and interactions inclusive of non-linearity. The reconstruction errors of the auto-encoder as it attempts to recreate the original distribution by means of regression will be minimal in the case of normal data instances. Anomalous data will result in larger reconstruction errors, and based on the selection of an appropriate threshold, anomalies or deviations from the normal behavior can be detected. A bidirectional layer can extend the traditional approach using relevant sequence information across two directions, i.e., past to future and future to past. In this work, AE models are constructed using LSTM and GRU separately with and without a bidirectional layer.

8. Results

To assess the regression performance of the deep learning networks, the four measures used are mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and coefficient of determination (R^2) as in Table 2. Lower scores indicate relatively better predictions for MAE, MSE, and RMSE, as it indicates fewer errors between actual and predicted values. R^2 is a measure of goodness of fit defined in the range of 0 and 1, where values closer to 1 exhibit better performance.

The GRU network, comprising three GRU cells (64, 32, and 16 units) with two dropout layers between adjacent cells and a fully connected layer with linear activation, achieved better results than its counterparts. It is hypothesized that the relatively simple nature of the dataset, in addition to the minor effects of seasonality/trend and generally stable behavior of the transformers, necessitated this model over complex approaches.

Table 2. Forecasting performance metrics for the deep learning methods.

Model	MAE	MSE	RMSE	R^2
GRU	21.71	10.00	33.80	0.67
GRU-AE	24.73	12.91	36.00	0.76
Bidirectional GRU-AE	23.7	12.11	35.00	0.63
LSTM	22.00	11.00	33.4	0.67
LSTM-AE	23.67	10.0	33.4	0.67
Bidirectional LSTM-AE	25.54	12.82	36.00	0.82

Table 3 reports the True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), and False Negative Rate (FNR) extracted from the confusion matrix during the classification of the 33 anomalies present.

Table 3. Anomaly detection performance metrics for the best methods.

Model	TPR	TNR	FPR	FNR
IF	100.00	98.15	0.00	1.84
One-Class SVM	87.50	97.15	2.85	12.50
GRU	63.62	82.48	36.44	17.50

It is observed that the IF model has the best performance in identifying both anomalous readings and normal readings with high TPR and TNR. This suggests a low prevalence of false positives and false negatives at inference. The results emphasize the robustness of IF in an unsupervised setting and its invariance to multiple inputs features' scaling. The IF predictions in Figure 8 appear to model the distribution density by proxy for effective differentiation.

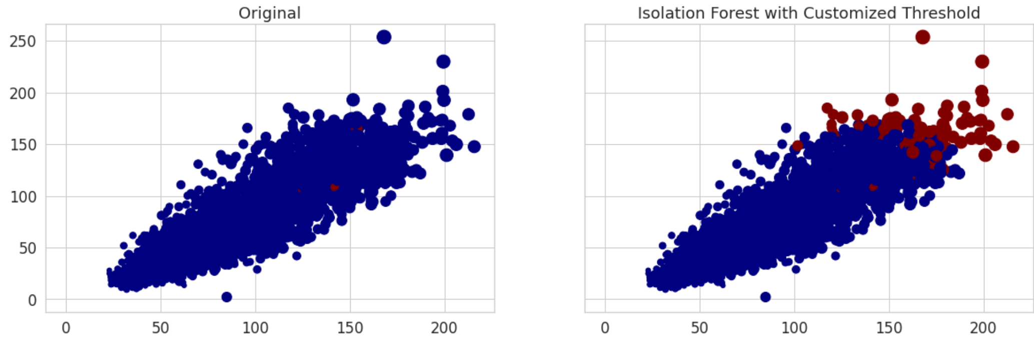

Figure 8. Original Dataset (**left**) versus Isolation Forest Predictions (**right**).

9. Discussion

9.1. Research Implications

Tracking, managing, and monitoring the operational measures of transformers is necessary for the effective distribution of electric power to residential and commercial levels. Generally, overheating is a serious concern due to the step-up/step-down voltage transformations dissipating heat throughout the core and windings. This phenomenon is exacerbated with poor oil heat transfer leading to insufficient cooling and circulation of the internal machinery. Insulation issues, mostly due to oil temperature anomalies, are reported to be one of the main factors of frequent transformer failures [35].

In alternate but analogous smart grid applications, the following studies were noted to be of pertinence to the field. The work in [36] utilizes clustering techniques and edge deployment to reduce the latency of a centralized model and perform anomaly detection for generic application-agnostic smart meters that can be deployed for any specific purpose. For anomaly detection in the performance of wind power grid integration and wind turbines, Ref. [37] tests an Ensemble Empirical Mode Decomposition-based neural network model on SCADA data acquired from a real wind farm and observes that abnormal behavior such as mechanical failures due to weather effects can be identified. Ref. [38] evaluated the performances of different machine learning and deep learning schemes for anomaly detection on photovoltaic components for timely disclosing abnormalities in solar power plants. The authors in [39] sought to detect distribution transformer parameters at a distance without using fitted multiple sensor arrays. This was completed through finding the optimum frequency representation for identifying the model, type and power rating with genetic algorithms and machine learning. They also posit the need for anomaly detection for the operational behavior of transformers and mention it as a vital future step.

We selected specific algorithms for testing and experimentation based on the frequency of their occurrences achieving acceptable performances in recent works. The unsupervised methods that we experiment with are representative of clustering, one-class learning and the supervised methods that involve neural networks (recurrent) and auto-encoders.

The rationale in comparing these varieties of algorithms is to establish the performances of vastly different model architectures for the task at hand, which has minimal apriori knowledge. A seminal survey [40] in the domain of anomaly detection enabled by smart sensors for energy consumption management outlines the following categories' techniques for modeling of normal behavior and identification of abnormalities. Another study [21] proposes anomaly detection with one-class SVM as one of the novel approaches with the purpose of diminishing energy expenditure in buildings. The same authors as the last work study the role of deep learning (with micromoments) for the detection of abnormal energy consumption within household appliances.

Big Data powered by machine learning and predictive analytics allow for informed decision making through timely warnings. The objective of this work was to implement an automated end-to-end IoT system with machine learning integrated anomaly detection for improved transformer maintenance and monitoring. While a plethora of recent work address the IoT aspects of transformers, energy management systems, and smart grids, few incorporate anomaly detection methods that are not reliant on static thresholding or probabilistic change-points. The advantage of machine learning lies in the ability to reasonably predict practical alarms without necessarily assuming time-series stationarity or minor variations in expected data distributions [41]. The IF algorithm leverages a combination of measurements and as such is posited to yield a better representation of the condition of transformers and provide higher value to utility providers and maintenance authorities. The one-class SVM and GRU models followed respectively in performance, with the former being quite close to IF and the latter giving more false positives, which is likely due to overfitting. We believe that our work addresses the relative scarcity of anomaly detection methods focused on distribution transformers, as they are key components (feeders especially) of the electric grid with its failures leading to energy loss, blackouts and other critical adverse effects to the immediate communities.

9.2. Limitations and Future Work

While this work attempts to bridge the well-researched paradigms of IoT and ML managing techniques seen in the smart grid domain with scarcer approaches of intelligent fault detection, it is not without limitations. Firstly, the number of anomalies in this dataset is very few (33), and their subtypes (root cause for fault) are not labeled. This might not be representative of all types of faults that the transformer can incur. Secondly, knowledge of day-to-day weather conditions could add more information to the model's prediction of normal readings and faults [42]. Lastly, the performance of the created model can deteriorate over time, specifically due to concept drift (significant changes in relationship between anomalies and predictor variables compared to training time) and data drift (significant changes in the distributions of the predictor variables) [43]. A prolonged deployment of this system can validate the robustness in a live setting.

The following statements present avenues for future work. A foremost phase would be to integrate forecasting and anomaly detection in the same system with even the same algorithm, since we can conduct both regression and reconstructive loss-based abnormality identification with the same RNN backbone [40]. The large distances between the distribution transformers and electrical plants render the former susceptible to cyberattacks wherein malicious hackers can capture real-time readings to distort transformer performance. Separating among this type of forced anomaly and different types of faults would offer more information to the stakeholders than communicating only "normal" or "anomaly". Inspired by the convolutional neural network-based fault classification approach implemented in [44], our next steps can look at fault stratification through multi-class classification as well. The IoT sensors we have utilized provide general operational information; however, more involved sensors can allow for advanced approaches such as dissolved gas analysis to generate additional insights regarding thermal and electrical stresses sustained by oil-immersed transformers. The authors in [45] apply different classification algorithms to diagnose power transformers based on parts-per-million of different gases present in the oil at a given time. However, this improved accuracy comes at an increased cost of sensors, and it is sensitive to the area (hospitals, houses, leisure venues) and subject to the priorities of the utility planner involved.

10. Conclusions

This work proposed an enhanced IoT-based real-time monitoring system for feeder-side distribution transformers to improve fault detection and provide timely alerts to maintain the reliability of the power distribution network. To achieve these objectives, the principles of Big Data processing and cloud services were utilized. The parameters of three-phase feeder currents, temperature, oil temperature/level, and geographical coordinates were collected in real time by a low-cost IoT module and made accessible through a cross-platform mobile application. Experimental results show the system is resilient, scalable, secure, and efficient in communicating relevant information to the utility providers. The Isolation Forest anomaly detection algorithm was found to detect 100% of the scarce anomalies in a large real-time dataset. A key advantage of this finding is that a standard IoT system collecting oil temperature and three-phase feeder currents in conjunction with a lightweight algorithm can predict anomalous behavior 24 h before. Future works will study techniques to reduce the number of IoT devices through the estimation and perform exhaustive testing across various modalities in a live setting.

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Abbreviations

The following abbreviations are used in this manuscript:

ADF	Augmented Dickey–Fuller
AE	Auto-encoders
ATI	Ambient Temperature Indicator
I2C	Inter-integrated Circuit Communication Protocol
FNR	False Negative Rate
FPR	False Positive Rate
GRU	Gated Recurrent Unit
IF	Isolation Forests
IoT	Internet of Things
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LoRa	Long-Range Wide-Area Network
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MSE	Mean Squared Error
MQTT	Message Queuing Telemetry Transport
OTI	Oil Temperature Indicator
OTT	Oil Temperature Trip

PSCAD	Power Systems Computer-Aided Design
R^2	Coefficient of Determination
RMS	Root Mean Square
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
RPi	Raspberry Single board Microcontroller
SCADA	Supervisory Control and Data Acquisition
SVM	One-Class Support Vector Machines
TPR	True Positive Rate
TNR	True Negative Rate
WTI	Winding Temperature Indicator

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