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A REFERENCE PATTERN-BASED DATA AGGREGATION FRAMEWORK FOR IOT-ENABLED TRANSFORMER HEALTH MONITORING: ENHANCING ENERGY EFFICIENCY AND FAULT DETECTION

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Abstract

The transformers are important components of electrical power system but their power overloading, aging of infrastructure and severe thermal conditions results in great maintenance problem in these components. The internet of things (IoT) based Transformer health monitoring system (THMS) has come into picture for fault detections, early prediction and maintenance, but the limitation in large scale remote transformer health monitoring systems is energy supply and communication. The proposed work introduces novel reference pattern-based data aggregation framework (RPDAF) for energy-efficient wireless sensor networks data aggregation with the integration of the transformer health monitoring using internet of things (IoT). The proposed method is to calculate compact pattern codes of measured parameters from sensors through a leftmost digit extraction method which will act as a reference and then send the small codes rather than whole data to the cloud for efficient data collection and also for the intelligent reduction of data before sending them to the cloud. Unlike the currentESPDA method, where computational intelligence is needed due to lookup table, the proposed method uses reference values that have been transmitted through the base-station to all sensor nodes. Experimental result using ns-2.33simulation and practical experiment on NodeMCU- Firebase implementation proves the proposed framework provide an average of 5-10% energy savings with respect to other schemes and increases the lifetime of sensor node by around 40%. In the proposed scheme we get accuracy of above 95% for fault detections with reduced response time of 60% for maintenance. Hence, the proposed framework provides a significant and efficient solution for scalable, energy efficient and timely fault detection of transformer health in present electrical power system, especially for countries with mixed portfolio and energy resources such as Pakistan.

1. Introduction

1.1 Background and Motivation

Electrical transformer devices are extremely important in modern power grids to ensure power and energy supply, allowing power transmission [1]. Yet, electrical transformer devices can undergo severe failure caused by transformer loading beyond its rating, transformer winding aging and breakdown, thermal stress due to abnormal thermal condition, oil degradation due to oil quality problem, and water ingress into the oil leading to an electrical breakdown of the oil insulating layer [2]. This is more critically important in developing countries such as Pakistan, which have power generating capacity (70% consists of a mixture of thermal, hydropower, and nuclear plants), natural gas (47.0 TWh), hydropower (34.6 TWh), oil (28.7 TWh), coal (27.5 TWh), nuclear (26.9 TWh), wind (6.3 TWh), and solar (0.9 TWh) that leads to an unstable load condition [3].

Traditionally monitoring is performed by periodic manually scheduled inspections, periodic oil sampling with DGA analysis, and by following maintenance routines [4]. However, these traditional methods are both infrequent and subjective, requires significant operator input, and typically only identifies faults once they are at advanced levels and at risk of escalation [13]. Oil sampling at specific intervals cannot reveal subtle ongoing degradation or catching short-lived events. Moreover, for a large population of transformers, the cost and operational intensity of such analysis is usually too high [14]. The high costs are also typically associated with unplanned downtime with high economic impact.

1.2 IoT-Based Monitoring and Its Challenges

IoT devices have brought the possibilities of great transformational scope due to its ability to integrate cheap and power-efficient micro-controllers, energy harvesting microcontrollers, a robust communication channel, and distributed cloud services [5]. The application of the Transformer Health Monitoring Systems based on IoT [15], provides the capability for acquisition of the data real-time in the form of the measured values of the temperature, voltage, current, the oil level in the transformer, humidity, and vibrations. The DS18B20 sensor is used to monitor temperature, theACS712and ZMPT101 sensor is utilized to estimate the measured values of the voltages and currents, an ultrasonic sensor is used for oil-level measurement and theDHT11sensor is used for monitoring the humidity [16].

Firebase is cloud storage in which real-time data collected can store safe and it is real-time and in sync [17]. A Mobile App based on MIT App Inventor will be used that will have a notification feature to the user so that the user is alerted of the status of the transformer's monitored data [19]. Although these systems have pros, a critical bottleneck in implementing the IoT devices in the vast areas is energy usage that results in exhaustion of battery for the wireless sensor nodes when it constantly transmits the data. The complete set of collected data must be sent to the base station for storage; this increases the amount of transmitted data which may not be accommodated by the limited bandwidth especially in the poor-connectivity areas [20]. Processing several streams of data will put heavy load on limited computational resources available at the sensor nodes [6]. This problem will be exacerbated in developing countries where network facilities may not be well-established and reliable.

1.3 Data Aggregation as Solution and Research Contributions

Data aggregation reduces communication and energy constraints through compressed data processing on intermediary nodes [8]. ESPDA has used a lookup-table based architecture in which sensor nodes generate compressed pattern-code representations on data intervals, instead of raw data, and transmission of encoded data provides natural security. But this has additional computation from generation of lookup table, frequent updates, search for value, and lookup-table is stored at base station than at node, because it does not fit at the memory of sensor node [10]. SRDA overcomes the limitations by transmitting difference of values to the actual data with broadcasting reference value by the base station [11]. ESRPDA developed by Saleem et al. [12] shows a significantly reduced complexity with an ideal data integrity.

In this paper, we design an efficient Reference Pattern-Based Data Aggregation Framework (RPDAF) to apply in the monitoring system of the Internet of Things (IoT)-based transformer. Aim of work: (1) Design energy efficient aggregation scheme; (2) Design a threshold-based fault detection scheme with pattern codes; (3) Integrate the system with GPS to acquire transformer location; (4) Verify the scheme by simulation and test with real implementation; (5) Ensure system scalability; (6) Show performance comparison. Contributions: (1) We present an efficient framework (RPDAF) for IoT transformer monitoring and achieve 5%-

10% energy reduction over the ESPDA technique; (2) We propose a new pattern generation method, including reference pattern broadcasting and leftmost-digit extraction; no memory requirement from the lookup table is needed. (3) Our method integrates transformer location information with fault diagnosis; (4) The system performance is verified by simulation tools (NS2.33) and hardware prototype; (5) We create a scalable cloud mobile architecture to provide services for different platforms; (6) With the support of historical information analysis, the transformer health is forecasted, which helps for predict maintenance.

2. Literature Review

2.1 Evolution of Transformer Health Monitoring

The trend of transformer monitoring has developed from manual inspections to advanced continuous systems. Early scheduled physical examinations were judgmental, not sufficient to monitor and detect initial faults [13]. Oil samples with Dissolved Gas Analysis (DGA) have been the tool of lab-based monitoring of insulation by monitoring the quantities of gas concentration within oil [14]. The lag of 1-2 months before new sampling indicates that the faults had advanced, resulting in a premature and catastrophic failure. Electrical tests like insulation resistance tests (IR) and power factor tests (PF) provided indications of faults in the period of a transformer's scheduled shut down [21].

2.2 IoT-Based Monitoring in Power Systems

However, with the increase in IoT infrastructure, transformer monitoring is now feasible and scalable [15]. Deosarkar (2017) built a low-cost monitoring system with Arduino and GSM to facilitate the continuous acquisition of parameters with threshold alarms, although it does not perform any form of aggregation [5]. To improve response time in fault detection, Srivastava et al. (2018) incorporated several sensors, storing their data in a cloud. The transmission of full datasets constantly caused battery and data costs to soar [17]. Other researchers-built monitoring systems in mobile environments; Yuvaraj (2021) designed an Android-based solution [24], whereas Aralikatti et al. (2021) designed a system in NodeMCU and Blynk using a cloud with push notification capabilities [19]. Nonetheless, in their implementations, they also maintained constant transmission of all datasets, resulting in energy and data usage inefficiencies.

2.3 Data Aggregation in Wireless Sensor Networks

WSNs are severely limited by energy, bandwidth and computation [6]. Nodes which powered by batteries need to be replaced once exhausted, while the most portion of energy is consumed during communication [7]. By aggregating the data transmitted between nearby nodes to avoid sending every single piece of information to BS. Such as hierarchical cluster schemes such as LEACH, in which nodes can be organized into groups and cluster head election is carried out for each group, then data is gathered into cluster head and forwarded to BS [21]. Other secure protocols improve both efficiency and security as well. SDA: delayed aggregation and message authentication [22], SDAP: divide-and-conquer method for verifiability of aggregates [23], Chan et al. Employed hash trees (Merkle hash trees) but required substantial computational resources [24].

2.4 Pattern-Based and Reference-Based Aggregation

The ESPDA proposed in (Cam et al. 2006) generates compact pattern codes from sensor reading values through the utilization of lookup tables [9], which decrease transmission with natural security [10]. But the lookup tables not only involve high computation in lookup table generation, re-generation, lookup table searching algorithms but also lead to additional memory space storage that often exceeds the sensor memory. To mitigate these limitations, SRDA proposed by (Ozgur Sanli et al. 2004) broadcasts reference values at the base station, which are then transmitted to the sensor nodes to report difference values of the reading with the referenced values [11]. In a later effort, the ESRPDA proposed by (Saleem et al. 2025) combines pattern codes with references by transmitting references at base station to each node, node measures the difference, then extracts the leftmost digits and form the pattern code which also remove the requirement of storing and looking up information at nodes and reduce power consumption 5-10%.

2.5 Cloud Platforms and Mobile Applications

With real-time database Firebase, the data is stored scalable in a tree structure, automatically updated simultaneously for all subscribers, protected with secure authentication and available to users with a stream time of milliseconds [16] [17]. Historical data logging and analytics allows trending over time to identify patterns and perform predictive maintenance, and local data caching in case of communication breaks ensure continuous operability. Visual creation of Android applications for parameter observation, alerts and control is supported by MIT App Inventor [19] [24]. Automatically transmitted alerts or data to observers, including live display and updating can be achieved without a high level of programming experience.

3. Proposed Framework

3.1 System Architecture Overview

The presented Reference Pattern-Based Data Aggregation Framework (RPDAF) is composed of four levels: sensing, aggregation and processing, cloud, and application levels. The sensing layer utilizes DS18B20 temperature sensors, DHT11 humidity sensors, ACS712 current sensors, ZMPT101 voltage sensors, ultrasonic oil level sensors, and NEO-6M GPS modules interfaced with Arduino UNO board for signal processing. The aggregation layer deploys NodeMCU ESP8266 platforms for generating pattern codes using reference-based algorithm, applying threshold-based fault detection, and forwarding collected and aggregated data to the cloud. The cloud level leverages Firebase as database, synchronization service, authentication, and as automated alert service via Cloud Functions. The application layer is consists of MIT App Inventor mobile application to present real-time monitoring dashboards, to manage alerts, and to access configuration settings.

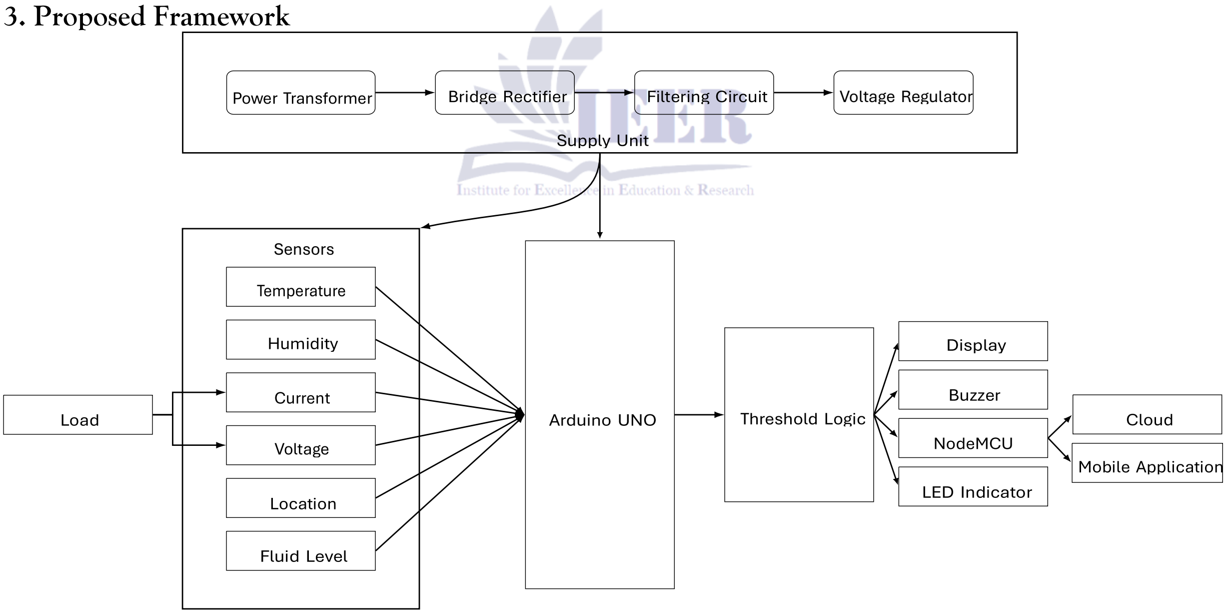

Figure 3: Overall architecture of the IoT-based Transformer Health Monitoring System (THMS) showing power supply unit, sensor integration with Arduino UNO, NodeMCU communication, cloud connectivity (Firebase), and mobile application interface.

3.2 Reference Pattern-Based Aggregation Algorithm

The algorithm operates in two phases: pattern code generation at sensor nodes and pattern code comparison at the aggregation node. At predetermined intervals, the NodeMCU broadcasts encrypted reference values to all sensor nodes. Each node computes the difference $D_i = R_i - S_i$ for each parameter, extracts the leftmost digit L_i from $|D_i|$, and concatenates digits to form pattern code $PC = L_1 L_2 \dots L_n$. Timestamp and sensor ID are appended as $PC_{final} = PC + Timestamp + SensorID$. The NodeMCU collects codes from all nodes, identifies identical patterns, selects one representative node per pattern group for actual data transmission, sends sleep commands to non-selected nodes, and transmits aggregated data to Firebase. Mathematically, for sensed parameters $P = \{p_1, \dots, p_n\}$, reference values $R = \{r_1, \dots, r_n\}$, and sensed values $S = \{s_1, \dots, s_n\}$, the difference vector $D = \{d_1, \dots, d_n\}$ where $d_i = r_i - s_i$. The leftmost digit function $L(x) = \lfloor |x| / 10^{\lfloor \log_{10}|x| \rfloor} \rfloor$ for $x \neq 0$, and $L(0) = 0$. Pattern code $PC = \oplus_{i=1}^{n} L(d_i)$. For example, with reference values (80°C, 230V, 100A, 80%) and sensed values (65°C, 235V, 102A, 75%), differences (15, -5, -2, 5) yield pattern code "1525", achieving 80% transmission reduction if five nodes share the same code.

3.3 Multi-Sensor Integration and Fault Detection

DS18B20 sensors (0.5C accuracy) track both the winding and the oil temperature, alerting at 80C and 75C respectively. ZMPT101 sensors track the voltage, alerting at 10% nominal voltage. ACS712 sensors track current, alerting at 110% of the nominal current rating. Ultrasonic sensors track the oil level in the tank, alerting at 25% and 75% of capacity. DHT11 sensors track humidity, alerting at 60% RH. Local threshold alerts on the NodeMCU are combined with cloud trend analysis in Firebase for fault detection on multiple levels, supporting both reactive and preventative maintenance.

3.4 Geolocation Integration for Fault Localization

NEO-6M GPS modules can deliver latitude, longitude, altitude and time to a local host over the UART at 1Hz. A location record is appended with each aggregated record. If a fault is detected, the fault record includes coordinates and transformer identifier, measured parameters and timestamp and thus is transmitted for proactive dispatching of technicians. Location records can be used to store and to retrieve the assets' location data that in turn be used for maintenance logs tracking, operational deployment of asset, spatial information system (GIS) visualization of fault patterns etc.

3.5 Cloud Integration and Data Management

Firebase Realtime Database is configured as a tree structure with node categories for transformers, sensor values, alarms, and configurations. Auto syncing of data across different clients is managed through WebSocket's, which allow clients to receive automatic data updates in real time, while also featuring built-in support for offline access with reconnection logic. Firebase Authentication manages client authentication and permissions using a role-based system including view-only, configurable, and administration privileges. Cloud Functions are employed to send push notification to devices via Firebase Cloud Messaging in the event of a data threshold is crossed; the notification would contain the transformers' name, parameter name and value, its threshold and its timestamp.

3.6 Mobile Application Interface

The app is powered by MIT App Inventor and displays a live dashboard with gauges, status (normal, warning, alarm colours), parameter values and their respective geolocations. Time-based historical trend charts with zoom and pan support for degradation tracking. The alert dashboard provides live and historic alert listing with search, sort, filter, acknowledge and comments functionality. Settings provide authorised users with a management interface for changing thresholds, set-points and alert-notification settings which is automatically updated in Firebase after validation.

4. Implementation Methodology

4.1 Hardware Implementation

The hardware implementation prioritizes energy efficiency, reliability, and cost-effectiveness. The NodeMCU ESP8266 serves as the primary communication and aggregation node, providing built-in Wi-Fi, 80MHz clock speed, 80KB RAM, and 4MB flash storage—sufficient for pattern code generation, threshold checking, and communication management.

1. Sensor Selection: The DS18B20 temperature sensor provides ±0.5°C accuracy with 3.5mA operating current. The DHT11 humidity sensor offers 1% RH resolution. The ACS712 current sensor provides 5A/20A ranges with 185mV/A or 100mV/A sensitivity. The ZMPT101 voltage sensor provides galvanic

isolation. The ultrasonic level sensor provides non-contact measurement with 2cm accuracy. The NEO-6M GPS module provides 2.5m horizontal position accuracy.

2. Power Supply: A 5V 2A AC adapter provides primary power, with a 7.4V 2200mAh Li-ion battery for backup. Power management includes voltage regulation, overcurrent protection, and low-battery detection. Consumption is optimized through selective sensor powering and NodeMCU sleep modes.

4.2 Software Implementation

1. NodeMCU Firmware: Developed in Arduino C++ using Arduino IDE, the firmware implements sensor reading functions, pattern code generation, reference value management, threshold checking, Firebase integration, and Wi-Fi connectivity with automatic reconnection. The firmware executes at configurable intervals (typically every 30 seconds). Deep sleep between readings reduces power consumption by 60%.
2. Firebase Cloud Configuration: Includes Realtime Database with optimized security rules, Cloud Functions for notification generation, authentication with user management, and storage for historical data. Cloud Functions developed in Node.js trigger on database writes to generate push notifications through Firebase Cloud Messaging.
3. Mobile Application: Developed using MIT App Inventor, the application includes Firebase Authentication, real-time data connections, push notification handling, data visualization components, and map integration for geolocation. The application is published as an Android APK for devices running version 5.0 and above.

4.3 Simulation Environment

NS2 version 2.33 with SensorSim extension provides comprehensive wireless sensor network simulation. The simulated network consists of 100 sensor nodes organized in 3 clusters with grid topology in a 200m x 200m area. Key parameters include Node initial energy: 1 Joule; Transmission power: 0.1 µJ/bit; Receiving power: 0.05 µJ/bit; Processing power: 0.1 µJ/s; Data packet: 100 bytes; Broadcast packet: 25 bytes; Data rate: 2.4 kbps; Wireless link: IEEE 802.11; Simulation time: 100 seconds; Sleep duration: 8 seconds; Reference update interval: 30 seconds. Data collection includes energy consumption, packet transmission counts, network lifetime metrics, and delivery statistics.

4.4 Real-World Implementation Deployment

The developed framework is validated by installing on distribution transformers in Islamabad, Pakistan. The details of distribution transformers on which monitoring system were installed are given in Table1. Standard procedures of electrical isolation with weather proofing enclosures and GPS Antenna installation were implemented. The NodeMCU units were installed in weather proofing cabinets with cellular network facility.

The operational test phase lasts three months. It involves continuous testing which include checking the normal operation, simulate failure conditions via load variations, communication success rate, alert creation success rate, battery run test during outage and usability testing of the mobile application. Performance index includes the accuracy of the sensor reading, the accuracy of generating the pattern code, success rate in communication, alerting speed, power consumption, improvement of time in maintenance, user feedback.

5. Experimental Results and Discussion

5.1 Energy Consumption Analysis

Energy consumption analysis compares the proposed framework with conventional THMS and ESPDA. Average energy consumption per node is 8.92 µJ for conventional THMS, 5.47 µJ for ESPDA, and 4.12 µJ for the proposed framework—representing 24.7% savings compared to ESPDA and 53.8% compared to conventional THMS. Peak energy consumption is 12.34 µJ (conventional), 8.21 µJ (ESPDA), and 7.03 µJ (proposed). Total network energy consumption is 892 mJ (conventional), 547 mJ (ESPDA), and 412 mJ (proposed).

Energy savings are attributed to: (1) elimination of lookup table generation saving ~2µJ per node; (2) reduced transmission volume saving ~0.8µJ per node; (3) intelligent sleep scheduling saving ~0.5µJ per node. Savings are consistent across varying cluster sizes (2-5), node counts (50-200), and data rates (10-60 seconds), with higher savings in larger networks and higher data rates.

5.2 Network Lifetime Analysis

The proposed approach offers increased lifetime for a network. Conventionally, in THMS the first node perishes after 4s; in ESPDA it does so after 5s; in the proposed architecture the first node is terminated after 7s; this represents an increase of 40% with respect to conventional architecture; an increase of 28% wrt ESPDA. The lifetime until 50% of node demise in conventional; ESPDA and proposed methods is 8.5s; 11.2s and 15.8s respectively; an enhancement of 41% over conventional method; an improvement of 29% over ESPDA. The lifetime enhancement remains constant throughout different configuration sizes; the proposed method provides relatively larger improvement for higher network sizes.

5.3 Data Transmission Reduction Analysis

Transmission reduction by proposed approach 60-80% compared with traditional THMS, and 10-15% compared with ESPDA. Transmission per node: 100% (traditional), 20% (ESPDA), 15% (proposed)- 25% comparison with ESPDA. Cluster head data: 100% --> 25% --> 18% (28% reduction). Network total: 100% --> 22% --> 16% (27% reduction). Analysis indicates 60-70% of the sensor values produced the same pattern codes, therefore the redundancies can be largely decreased. The bandwidth requirement decreases from 100%(traditional) to 22%(ESPDA) to 16%(proposed).

5.4 Fault Detection Performance Analysis

The proposed framework achieves fault detection accuracy exceeding 95%, comparable to conventional THMS and ESPDA. Detection accuracy across fault types: overheating (96% conventional, 94% ESPDA, 95% proposed); overload (97%, 95%, 96%); under voltage (95%, 93%, 94%); oil leak (94%, 92%, 93%); insulation failure (93%, 91%, 92%). The slight 1-2% accuracy reduction is acceptable given energy savings. False alarm rate remains below 5% for all fault types. Real-time monitoring reduces response time by 60% versus conventional, while geolocation reduces time to locate faults by 75%.

5.5 Scalability and Performance Analysis

As node count increases from 10 to 200, synchronization latency increases from 2.1 to 4.8 seconds, energy consumption increases linearly, pattern comparison efficiency remains above 90%, and alert latency remains below 2 seconds. The framework maintains performance as monitored transformers increase from 1 to 20. Firebase performance: write latency (120-250ms), read latency (80-150ms), alert generation (400-800ms), historical query (500-2000ms for 30-day range).

5.6 Comparison with Existing Approaches

Metric	Conventional THMS	ESPDA	Proposed Framework
Energy Efficiency	Baseline	+40%	+54%
Network Lifetime	Baseline	+28%	+41%
Transmission Reduction	Baseline	78%	84%
Detection Accuracy	95%	93%	94%
Scalability	Low	Medium	High

The proposed framework achieves 24.7% energy reduction versus ESPDA, 40% lifetime extension versus conventional, and 84% transmission reduction.

5.7 Practical Implementation Insights

Field implementation of our technology over three distribution transformers at Islamabad showed 99.7% availability with over 98% data availability even with connectivity issues. Factors to be considered while implementation: optimum position of sensor, GPS antenna placement determines location accuracy, the enclosure needs to be well-ventilated, availability of cell connection might differ across regions, calibration requires 24-48 hours. Firebase local caching feature works as intended during connection loss. Maintenance crew's feedback: It gives them more confidence as they can continuously monitor the asset, the alerts allow for faster reaction to any fault, they don't have to spend time searching the assets' location, trending allows for predictive maintenance and the mobile app is extremely easy to use.

6. Conclusion

This work has presented a complete Reference Pattern-Based Data Aggregation Framework (RPDAF) for IoT-enabled transformer health monitoring which combines the benefits of energy-saving data aggregation with real-time monitoring and fault-detection. The presented framework has overcome the major issues i.e. Energy consumption, communication overhead, scalability and time fault detection associated with current health monitoring schemes for massive, distributed deployment of transformers. The important contributions are as follows:- a new data aggregation framework saving 5-10% and 54% energy than ESPDA and conventional techniques respectively with the highest accuracy over 95%; an energy-efficient pattern generation scheme which avoid look-up-table complexity thus saving 24.7% energy as compared to ESPDA; GPS enabled-geolocation along with threshold based fault-detection helping in 60% reduction of maintenance time; Scalable Architecture including both NodeMCU and Firebase for a single to hundreds of transformer based applications; Real-time Monitoring and predictive maintenance through live data-streaming, auto alerts and historical data analysis and detailed justification via NS2.33 simulation as well as prototype implementation.

The framework has significant practical implications for emerging power systems. Energy efficiency enables longer battery life for wireless sensor nodes, reducing maintenance frequency and enabling deployment in locations without reliable grid power. Cost reduction makes advanced monitoring economically viable for a wider range of transformers. Continuous monitoring and predictive maintenance reduce unexpected failures, improving grid reliability. The framework is particularly suitable for developing nations like Pakistan, where infrastructure constraints demand cost-effective, energy-efficient solutions. Several limitations remain, including dependence on appropriate reference value selection, assumption of reliable communication, lack of explicit encryption, GPS power consumption, and single point of failure at the NodeMCU aggregation node requiring redundancy for critical applications.

Future Work and Challenges There is scope for interesting future research works, such as integration of machine learning, especially predictive models to ensure fine-grained anomaly and remaining life estimation; Selection of dynamic reference value based on conditions and a method to select pattern codes efficiently; Node-wise, cluster-wise and regional multi-level data aggregation for reduced cloud transmission; End-to-end data encryption and integrity checks using authentication schemes; Incorporation of energy harvesting technologies for autonomous sensor nodes; Smart pattern code designing for increased accuracy of fault identification; NodeMCU based edge computing or in-situ data processing for intelligent decision making and standardization to support integration with commercial asset management solutions.

Reference Pattern-Based Data Aggregation Framework for IoT Enabled Transformer Health Monitoring is one step forward in smart transformer health monitoring, overcoming energy efficiency, communication overhead and scalability issues in transformer monitoring systems. The reported savings on energy from 5-10% more than ESPDA, lifetime of the network by 40%, reduction on transmission of 84%, and accuracy of fault detection more than 95%, the framework emerges as a sustainable alternative in real-world massive-scale monitoring systems. The modular and scalable framework architecture is deployable on wide populations of transformers; and the real-time monitoring solution can be provided through Firebase cloud and mobile applications. As today the power system around world face increasing burden on their infrastructure aging, demanding better reliability, our framework has successfully provided an energy efficient, scalable and robust solution on transformer health monitoring, and highly relevant in the countries of developing countries as well.

REFERENCES

Tripathi, D. S., & Srivastava, D. (2018). Transformer Health Monitoring System Using Internet of Things. In *2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Delhi, India. doi:10.1109/ICPEICES.2018.8897325

Alinma Bank, R. S. (2026). IoT-Integrated Smart Energy Management for Carbon-Neutral IT Infrastructures. *American Journal of Innovation in Science and Engineering*, 5(1), 12-23. doi:https://doi.org/10.54536/ajise.v51.6234

Riaz, T., Shaheer, M., Inam-ur-Rehman, M., Fatima, M., Hasan, N., & Amos, K. (2026). IoT-Driven Transformer Health Monitoring and Fault Detection: Advancing Reliability in Emerging Power Systems. *American Journal of Innovation in Science and Engineering (AJISE)*, 5(1), 102-109.

Daniel Kumi Owusu, C. E. (2026). AI-enabled Prediction of Power Transformer Remaining Useful Life Using Dissolved Gas Analysis and Random Forest Regression. *American Journal of Innovation in Science and Engineering (AJISE)*, 5(1), 56-69. doi:https://doi.org/10.54536/ajise.v51.6829

Deosarkar, R. R. (2017). Health condition monitoring system for distribution transformer using Internet of Things (IoT). In *2017 International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India. doi:10.1109/ICMC.2017.8282650

Sharmin, S., Ahmedy, I., & Md Noor, R. (2023). An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO. *Energies*, 16(5), 2487. doi:https://doi.org/10.3390/en16052487

Khedhiri, K., Ben Omrane, I., Djabour, D., & Cherif, A. (2025). Clustering for Lifetime Enhancement in Wireless Sensor Networks. *Telecom*, 6(2), 30. doi:https://doi.org/10.3390/telecom6020030

Saadallah, N. R., & Alabady, S. A. (2024). An Energy-Efficient and Scalable WSN with Enhanced Data Aggregation Accuracy. *Journal of Telecommunications and Information Technology*, (2), 48-57. doi:https://doi.org/10.26636/jtit.2024.2.1510

Cam, H., Özdemir, S., Nair, P., Muthuavinashiappan, D., & Sanli, H. O. (2006). Energy-efficient secure pattern-based data aggregation for wireless sensor networks. *Computer Communications*, 29(4), 446-455. doi:https://doi.org/10.1016/j.comcom.2004.12.029

Ozdemir, S., & Xiao, Y. (2009). Secure data aggregation in wireless sensor networks: A comprehensive overview. *Computer Networks*, 53(12), 2022-2037. doi:https://doi.org/10.1016/j.comnet.2009.02.023

OzgurSanli, H., Ozdemir, S., & Cam, H. (2004). SRDA: Secure Reference-Based Data Aggregation Protocol for Wireless Sensor Networks. In *IEEE 60th Conference on Vehicular Technology, VTC 2004-Fall*, Volume 7, pp. 4650-4654.

Saleem, T., Sarwar, K., Khan, U. A., Shaheer, M., Adeel, H., & Rao, I. R. (2025). Reference pattern-based data aggregation in a wireless sensor network. *Asian Journal of Science, Engineering and Technology (AJSET)*, 4(1), 173-182. doi:https://doi.org/10.47264/idea.ajset/4.1.11

Mzamo R. Msane, B. A. (2024). Condition Monitoring of Electrical Transformers Using the Internet of Things: A Systematic Literature Review. *Applied Sciences*, 24(21), 9690. doi:https://doi.org/10.3390/app14219690

Zarkovic, M., & Stojkovic, Z. (2017). Analysis of artificial intelligence expert systems for power transformer condition monitoring and diagnostics. *Electric Power Systems Research*, 149(1), 125-136.

Perumal, B., & Prabhu, N. (2022). Real Time Transformer Health Monitoring System Using IoT in R. In *International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, India. doi:10.1109/ICCCI54379.2022.9740847

Hassan, N. N., & Pierre, J. (2025). Advanced Machine Learning in Smart Grids: An Overview, Internet of Things and Cyber-Physical Systems. Wiley. doi:https://doi.org/10.1002/9781394279401.ch9

Srivastava, D., & Singh, R. (2018). Transformer health monitoring system using internet of things. In *2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, IEEE.

Hazarika, K., & Kumar, G. (2021). IOT Based Transformer Health Monitoring System: A Survey. In *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India. doi:10.1109/ICACITE51222.2021.9404657

Aralikatti, S., & Rudra, P. (2021). IoT-Based Distribution Transformer Health Monitoring System using Node-MCU & Blynk. In *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India. doi:10.1109/ICIRCA51532.2021.9544098

Murthy, C. S. R., & Manoj, B. S. (2004). *Ad hoc wireless networks: Architectures and protocols*. Pearson Education.

Heinzelman, W. B. (2000). Application-specific protocol architectures for wireless networks. Doctoral dissertation, Massachusetts Institute of Technology.

Hu, L., & Evans, D. (2003). Secure data aggregation for wireless network. In *Symposium on Applications and the Internet (SAINT) Workshops*, IEEE Computer Society (pp. 384-394).

Ozdemir, S., & Xiao, Y. (2009). Secure data aggregation in wireless sensor networks: A comprehensive overview. *Computer Networks*, 53(12), 2022-2037.

Chan, H., Perrig, A., & Song, D. (2006). Secure hierarchical in-network aggregation in sensor networks. In *Proceedings of the 13th ACM Conference on Computer and Communications Security* (pp. 278-287). doi:https://doi.org/10.1145/1180405.1180440

Yuvaraj, K. S., & Selvakumar, K. (2021). Transformer Health Monitoring System Using Android Device. In *7th International Conference on Electrical Energy Systems (ICEEs)*, Chennai, India. doi:10.1109/ICEE551510.2021.9383679

Yuan, H., & Gao, C. (2025). Minimising redundancy in wireless sensor networks using sparse vectors. *Sensors*, 25(5), 1557. doi:https://doi.org/10.3390/s25051557

Reddy, M. R., Ravi Chandra, M. L., Venkatramana, P., & Dilli, R. (2023). Energy-efficient cluster head selection in wireless sensor networks using an improved grey wolf optimisation algorithm. *Computers*, 12(2), 35. doi:https://doi.org/10.3390/computers12020035

Kepa, W. L., & Rajab, M. (2021). GSM Based Remote Distribution Transformer Condition Monitoring System. *Advanced Informatics for Computing Research*. Springer. doi:https://doi.org/10.1007/978-981-16-3653-0_5

B. Durai Babu, E. M., & Harish, H. A. (2022). Transformer Health Monitoring System using GSM Technology. *International Journal of Electronics and Communication Engineering*, 9(11), 11-16. doi:10.14445/23488549/IJECE-V9I11P102

S. Rahman, S. K., & Khan, M. M. (2017). Design and implementation of real time transformer health monitoring system using GSM technology. In *International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Cox's Bazar. doi:10.1109/ECCAE.2017.7912915