WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Smart Transformer with IoT Monitoring: Design and Simulation of a Real-Time Condition Monitoring System

[Raut Jagdish Balu][1] ,[Shruti Sunil Bunge][2]and [Dhanshri Shantaram Dhanwate][3]

Department of Electrical Engineering, NIT's Late Annasaheb Patil,Polytechnic,Nashik,Maharashtra,India
jagdhishraut97@gmail.com, *shrutibunge30@gmail.com*, dhanshridhanwate96@gmail.com

ABSTRACT—

Distribution transformers are among the most critical and most heavily loaded assets of the power network, yet in many utilities they are still inspected manually at long intervals, so overloads, overheating and cooling faults often go unnoticed until a failure occurs. This paper presents the design of a smart distribution transformer monitoring system based on the Internet of Things (IoT). An ESP32 microcontroller acquires phase voltages and currents, oil and ambient temperature, vibration and oil level, estimates the hot-spot temperature and insulation ageing rate with the IEC 60076-7 thermal model, and publishes the data over MQTT to a cloud dashboard with SMS and mobile alerts. The system is evaluated by simulation of a 100 kVA, 11/0.433 kV transformer on a hot-season day with an evening overload. Without any response, the hot-spot temperature reaches 123.9 °C and the insulation ages 37.7 equivalent hours in one day; an IoT alert followed by a 15% load transfer reduces this to 22.5 hours, a 40.4% reduction. A residual-based check detects an injected 30% cooling degradation within 3.5 h, and data usage at a 10 s publishing interval is estimated at 45 MB per month. The design uses low-cost components and is suitable for retrofitting on existing transformers.

***Index Terms*—condition monitoring, distribution transformer, ESP32, hot-spot temperature, Internet of Things, MQTT, smart grid.**

I. Introduction

The distribution transformer is the last major link between the high-voltage network and the consumer. A utility may operate thousands of them, and each one is expected to run for 25 years or more with very little attention. In practice, distribution transformers are exposed to overloading, unbalanced loads, heat, moisture and poor maintenance, and their failure leads to long outages, loss of revenue and sometimes fire or oil spillage [1], [2]. In many rural and semi-urban feeders the only monitoring is an occasional visit by a lineman to read the oil-temperature dial, so abnormal conditions can develop for hours or days without being noticed.

The Internet of Things (IoT) offers a low-cost answer to this problem. Inexpensive sensors and Wi-Fi or cellular-enabled microcontrollers can measure the condition of each transformer continuously and send the data to a central server, where it can be stored, analysed and used to raise alarms [3]. IoT-based monitoring is also an enabling technology of the smart grid, which depends on two-way communication between field devices and control centres [4]. A transformer that reports its own loading, temperature and health in this way can be called a smart transformer.

This paper presents the design and evaluation of an IoT-based smart transformer monitoring system for a 100 kVA, 11/0.433 kV oil-immersed distribution transformer. The main contributions are: (i) a hardware and software architecture built from low-cost components; (ii) the use of the IEC 60076-7 thermal model on the microcontroller to estimate hot-spot temperature and insulation ageing in real time; (iii) a residual-based method for detecting cooling faults and sensor faults; and (iv) a simulation study that quantifies the benefit of an IoT alert on a hot-season overload day. Section II reviews the background, Section III describes the system design, Section IV the evaluation method, Section V the results, Section VI the challenges and future scope, and Section VII concludes the paper.

II. Background and Related Work

A. Transformer Condition Monitoring

Condition monitoring of power transformers has traditionally relied on periodic oil sampling, dissolved gas analysis (DGA), insulation resistance tests and visual inspection [1]. DGA remains the most informative method for detecting incipient internal faults, and its interpretation is standardised in [5]. However, laboratory tests are expensive, are carried out at intervals of months or years, and are mostly applied to large power transformers. For distribution transformers, which are numerous and low in value individually, the practical approach is to monitor a small set of inexpensive online parameters: load current and voltage, oil and ambient temperature, oil level and, optionally, vibration. These quantities already reveal the most common causes of distribution transformer failure, namely overloading, phase unbalance and loss of cooling [2].

B. Thermal Model and Insulation Ageing

The life of a transformer is determined mainly by the thermal ageing of its paper insulation, which depends on the winding hot-spot temperature. The loading guides IEC 60076-7 [6] and IEEE C57.91 [7] give an exponential model for estimating the top-oil and hot-spot temperatures from the load and the ambient temperature, and similar dynamic models have been compared in the literature [8]. The load factor is defined as the ratio of load apparent power to rated apparent power,

$$K = \sqrt{3}\, V_L\, I_L / S_r \qquad (1)$$

where V_L and I_L are the measured line voltage and current and S_r is the rated capacity. The efficiency of the transformer at load factor K and power factor $\cos\varphi$ is

$$\eta = K S_r \cos\varphi / (K S_r \cos\varphi + P_{fe} + K^2 P_{cu}) \quad (2)$$

where P_{fe} is the constant core loss and P_{cu} is the copper loss at rated load. Efficiency is highest when the copper loss equals the core loss, i.e. at

$$K_{\eta,max} = \sqrt{(P_{fe} / P_{cu})} \quad (3)$$

The ultimate top-oil temperature rise over ambient at load factor K is

$$\Delta\Theta_u = \Delta\Theta_{or} [(1 + R K^2) / (1 + R)]^x \quad (4)$$

where $\Delta\Theta_{or}$ is the rated top-oil rise, R is the ratio of load loss to no-load loss and x is the oil exponent. Because the oil has thermal inertia, the actual top-oil temperature Θ_o follows a first-order response with time constant τ_o:

$$\tau_o (d\Theta_o/dt) = \Theta_a + \Delta\Theta_u - \Theta_o \quad (5)$$

The hot-spot temperature is obtained by adding the winding gradient,

$$\Theta_h = \Theta_o + H g_r K^y \quad (6)$$

where H is the hot-spot factor, g_r the rated winding-to-oil gradient and y the winding exponent. For non-thermally upgraded paper, the relative ageing rate, which is the ratio of the actual ageing rate to that at the reference hot-spot temperature of 98 °C, is

$$V = 2^{(\Theta h - 98)/6} \quad (7)$$

and the equivalent ageing over a period is the sum of V multiplied by the time step,

$$L = \Sigma V_k \Delta t \quad (8)$$

A day in which L exceeds 24 h means that the insulation has aged faster than the normal rate on that day. Equation (7) shows that every 6 °C rise of the hot-spot temperature doubles the rate of ageing, which is why even a short overload on a hot day is costly. The temperature-rise limits of the standard are given in [9].

C. IoT Communication

MQTT, a lightweight publish–subscribe protocol standardised by OASIS [10], is well suited to constrained devices and unreliable networks. A device publishes small messages on named topics to a broker, and any dashboard, database or rule engine can subscribe. Quality-of-service level 1 guarantees at-least-once delivery, and a last-will message lets the broker announce when a device has gone offline. These properties make MQTT a common choice for IoT monitoring of field assets.

III. System Design

A. Overall Architecture

The proposed system has five layers, shown in Fig. 1. Sensors mounted on the transformer measure electrical and thermal quantities; an ESP32 edge node reads the sensors, runs the thermal model and decides locally whether any limit is exceeded; the data are sent through Wi-Fi, or through a GSM modem where Wi-Fi is not available, to an MQTT broker and time-series database; a rule engine generates alerts; and users view the data on a dashboard or receive an SMS or mobile message. Local decision-making at the edge is important because a transformer must be protected even when the network is down.

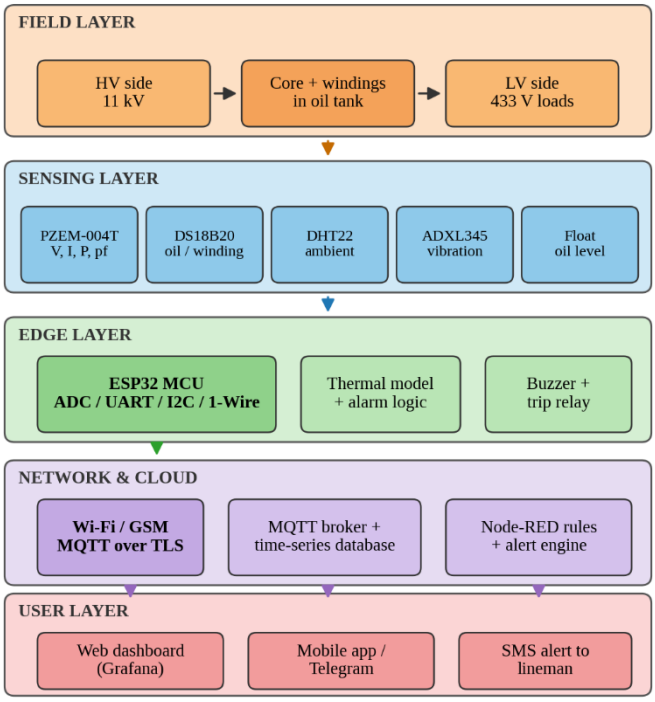


Fig. 1. Layered architecture of the proposed IoT-based smart transformer monitoring system.

B. Hardware

The components, listed in Table I, were chosen for low cost, easy availability and well-documented interfaces. The ESP32 [11] provides a dual-core processor, Wi-Fi and enough input/output for all sensors. A PZEM-004T module on each phase measures voltage, current, active power and power

factor through a split-core current transformer, which can be clamped around the LV cable without disconnecting it. The DS18B20 digital thermometer [12] has a range of −55 to +125 °C, which covers the full oil-temperature range; one probe is placed in the top-oil thermowell and a second on the tank wall near the winding. Because the hot-spot inside the winding cannot be measured directly with such a sensor, it is calculated from the model of Section II-B. All electronics are located on the LV side and in a separate enclosure, away from the HV terminals, and installation on a live transformer must be done only by authorised personnel following the utility's safety procedures.

TABLE I

Main Components of the Monitoring Unit

Component	Parameter / role	Interface
ESP32 DevKit	Edge computing, Wi-Fi connectivity	—
PZEM-004T (one per phase)	Voltage, current, power, power factor, energy	UART (Modbus-RTU)
DS18B20 (two probes)	Top-oil and tank-wall temperature	1-Wire
DHT22	Ambient temperature and humidity	Digital
ADXL345	Three-axis tank vibration	I²C
Float switch	Low oil-level detection	Digital input
SIM800L GSM module	SMS and data fallback	UART
Relay and buzzer	Local alarm; load-transfer or trip signal	GPIO

The estimated component cost of one unit is [insert total from the bill of materials] rupees, which is small compared with the cost of the transformer it protects.

C. Firmware and Data Flow

The firmware, written with the Arduino framework, follows the flowchart of Fig. 2. After initialisation, the node reads all sensors once per sampling period, computes the load factor from (1), updates the top-oil and hot-spot temperatures from (5) and (6) using a discrete form of the model, and compares the results with the limits of Table II. In normal operation one JSON message is published to the topic tx/TR01/telemetry every T_s seconds. If any limit is exceeded, an alarm message is published immediately, the buzzer is sounded and, for critical conditions, the relay output is activated. If the connection is lost, readings are stored in flash memory and sent later, and a hardware watchdog restarts the microcontroller if the program hangs.

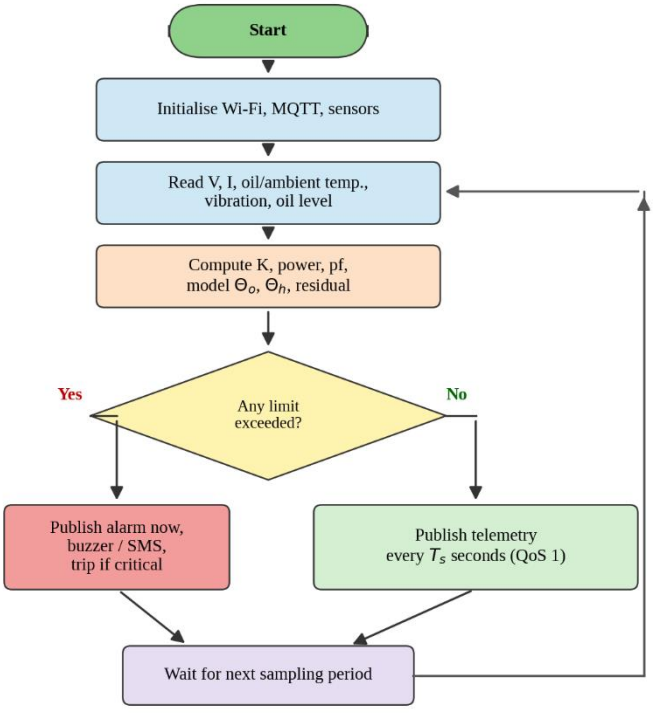


Fig. 2. Flowchart of the firmware running on the ESP32 edge node.

D. Alert Logic

Two alert levels are used: a warning that informs the operator, and an alarm that requires action. The limits in Table II are design settings based on common practice for oil-immersed distribution transformers, and they can be changed remotely. The hot-spot limit of 120 °C corresponds to the upper limit usually accepted for normal cyclic loading in [6]. The residual alarm is explained in Section IV-D.

TABLE II

Alert Thresholds and Actions

Parameter	Warning	Alarm	Action
Top-oil temperature	80 °C	90 °C	Dashboard flag; SMS at alarm
Hot-spot (model)	110 °C	120 °C	SMS; request load transfer at alarm
Load factor K	0.9	1.1	SMS; check for overload or unbalance
Model residual	—	6 K / 15 min	Inspect cooling and sensors
Oil level	—	Low switch	Immediate SMS; site inspection
Vibration	—	> 2× baseline	Inspect core and tank fastenings

E. Communication and Security

Each message is a compact JSON object carrying the device identifier, a time stamp, three phase voltages and currents, power, power factor, top-oil, tank-wall and ambient temperatures, humidity, oil-level state and vibration level. A typical message is 149 bytes long and the MQTT packet adds about 23 bytes of header and topic. Messages are sent with QoS 1 over a TLS-encrypted connection, and the device authenticates to the broker with its own user name and password or certificate, so that a stolen credential affects only one device. Time is synchronised from a network time server so that readings from different transformers can be compared.

IV. Evaluation Method

A. Transformer Model and Parameters

Because tests on a live distribution transformer with deliberate overloads are not practical, the monitoring logic was evaluated by simulation. A 100 kVA, 11/0.433 kV, ONAN (oil natural, air natural) transformer typical of distribution feeders in India [13] is modelled with equations (1)–(8), integrated with a time step of 1 min. The thermal parameters in Table III are typical values for this class of transformer from [6]; the loss values are assumed typical figures. The rated LV current is 133 A. The model was run for four consecutive identical days, and the results of the last day are reported so that the initial condition has no influence.

TABLE III

Simulation Parameters

Parameter	Value
Rating / voltage / cooling	100 kVA, 11/0.433 kV, ONAN
No-load loss P_{fe} / load loss P_{cu}	260 W / 1,760 W
Rated top-oil rise $\Delta\Theta_{or}$	55 K
Loss ratio R; exponents x, y	5; 0.8, 1.6
Oil time constant τ_o	180 min
Gradient g_r; hot-spot factor H	23 K; 1.1
Ambient temperature range	27–39 °C (sinusoidal)
Alarm response delay	10 min
Load transferred on alarm	15 %
Injected cooling fault	+30 % top-oil rise from 10:00
Sensor noise (standard deviation)	0.4 K

B. Load and Ambient Profile

A hot-season day was assumed, with an ambient temperature varying between 27 and 39 °C and a load that has a morning peak, an afternoon peak and a large evening peak caused by domestic cooling and lighting load, as shown in Fig. 3. The load factor reaches 1.25 at about 20:00 and is above rated for about 2 h 40 min in total. The daily average load factor is 0.65. This profile is a synthetic representation, chosen to include a realistic overload, and not a recording from a particular feeder.

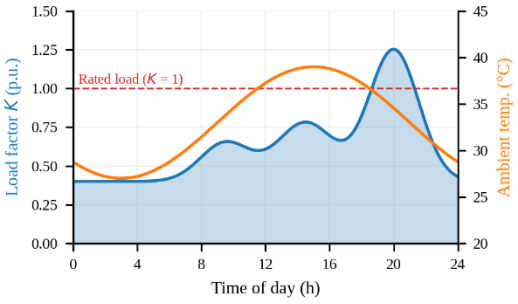


Fig. 3. Assumed 24-hour load factor and ambient temperature profile used in the simulation.

C. Scenarios A and B

Two scenarios are compared for the same load. In scenario A, the transformer is not monitored and no action is taken. In scenario B, the IoT system raises an alarm when the calculated hot-spot temperature reaches 120 °C. After a response delay of 10 min, which represents the time for the alert to reach the operator and for a load transfer or load-shedding action to be carried out, 15% of the load is removed. The load is restored when the hot-spot falls below 110 °C. The two scenarios are compared by their peak temperatures, the time above 120 °C and the equivalent ageing from (8).

D. Residual-Based Fault Detection

A measured oil temperature that departs from the model prediction indicates either a cooling problem, such as a blocked radiator, low oil level or a failed fan, or a sensor fault. The residual is defined as

$$r(t) = \Theta_{o,meas}(t) - \Theta_{o,model}(t) \qquad (9)$$

where the model uses the measured load and ambient temperature. To avoid false alarms from sensor noise, the residual is averaged over 5 min and an alarm is raised if the average stays above 6 K for 15 min. To test the method, a cooling fault was injected at 10:00 by increasing the top-oil rise by 30%, and Gaussian noise of 0.4 K standard deviation was added to the simulated oil-temperature sensor.

V. Results and Discussion

A. Efficiency

Figure 4 shows the efficiency calculated from (2). At rated load and a power factor of 0.9, the efficiency is 97.80%, and the maximum efficiency of 98.52% occurs at a load factor of 0.38 from (3). The curves are flat over a wide range of load, so efficiency is not a limiting factor in operation, but the lower efficiency at poor power factor shows the value of the power-factor measurement, which allows the utility to identify feeders that need capacitor compensation.

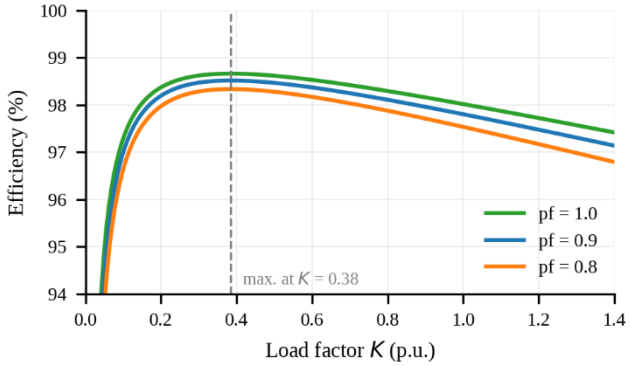


Fig. 4. Calculated efficiency of the 100 kVA transformer versus load factor for three power factors.

B. Temperature and Ageing

Figure 5 shows the simulated temperatures. In scenario A, the evening overload drives the top-oil temperature to 91.2 °C, above the 90 °C alarm, and the hot-spot to 123.9 °C, with 76 min spent above 120 °C. The time constant of the oil of 3 h explains why the peak temperature occurs after the peak load and why a short overload is much less harmful than a long one. In scenario B, the alarm is raised at 19:46 when the hot-spot reaches 120 °C, and the load transfer takes effect at 19:56. The peak hot-spot temperature falls to 121.9 °C and the time above 120 °C falls to 11 min, a reduction of 86%.

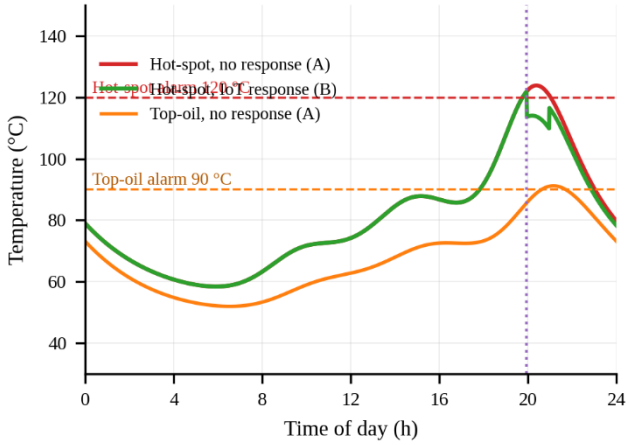


Fig. 5. Simulated top-oil and hot-spot temperatures without (A) and with (B) IoT-based alert and load transfer. The dotted vertical line marks the load-transfer time.

TABLE IV

Comparison of Scenarios A and B

Metric	A	B	Change
Peak top-oil temperature (°C)	91.2	87.4	−3.7 °C
Peak hot-spot temperature (°C)	123.9	121.9	−2.0 °C
Time above 120 °C (min)	76	11	−86 %
Time above 110 °C (min)	155	141	−9 %
Equivalent ageing (h/day)	37.7	22.5	−40.4 %

The effect on ageing, summarised in Fig. 6, is larger than the effect on peak temperature because of the exponential relation in (7). The equivalent ageing falls from 37.7 h to 22.5 h on this day, a reduction of 40.4%. The ageing of 37.7 h in 24 h means that the insulation consumed about 1.6 days of life in one day. This is a severe day, and normal days would give much lower values, but a feeder that is overloaded in every hot season would accumulate such losses repeatedly. The hot-spot in scenario B still slightly exceeds 120 °C because of the 10 min response delay, which shows that the speed of the alert and of the operator's response is as important as the monitoring itself. Utilities should therefore combine the alert with a pre-agreed action, such as automatic load transfer to a neighbouring transformer.

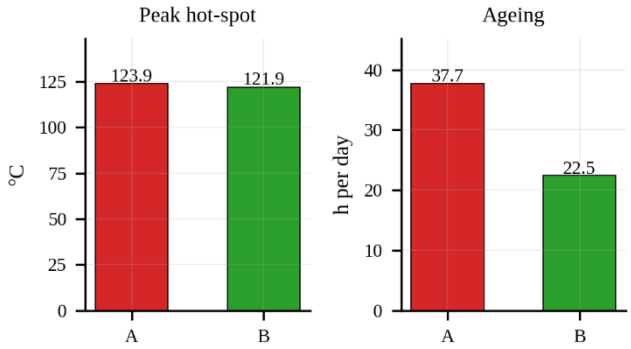


Fig. 6. Peak hot-spot temperature and equivalent ageing for scenarios A (no response) and B (IoT alert and load transfer).

C. Fault Detection

Figure 7 shows the residual-based detection of the injected cooling fault. Before 10:00 the measured oil temperature follows the model within the sensor noise, and the residual is close to zero. After the fault, the oil temperature starts to rise above the prediction, and since the oil responds with a time constant of 3 h the residual grows gradually, reaching 17.6 K at its maximum later in the day. The alarm condition of 6 K for 15 min is satisfied at 13:30, that is 3.5 h after the fault began, and well before the oil temperature itself would exceed an absolute alarm limit in this scenario. This type of early warning is a benefit of comparing measurements with a model, and cannot be obtained with a simple dial thermometer.

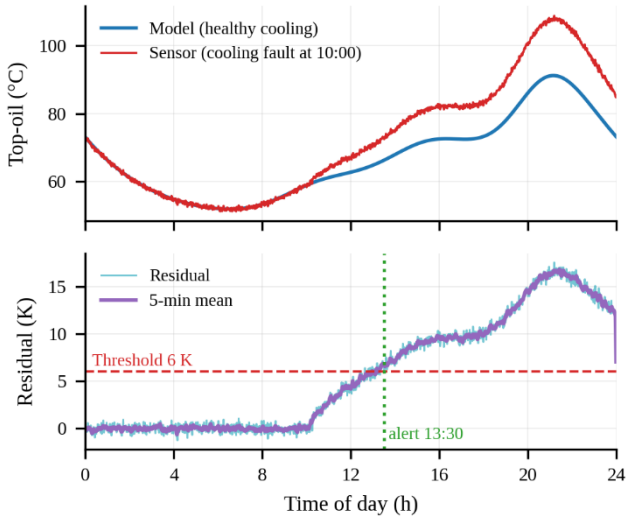


Fig. 7. Residual-based detection of an injected cooling fault: (top) model and noisy sensor oil temperature; (bottom) residual, its 5-minute mean and the alarm threshold.

D. Communication Data Usage

Figure 8 shows the estimated monthly data volume at different publishing intervals, calculated from the message size of Section III-E. At 10 s, the volume is about 45 MB per month, which is easily handled by Wi-Fi but is large for a prepaid GSM data plan, whereas 60 s gives about 7.4 MB. A practical compromise is to publish every 60 s in normal conditions and to switch to 5 s or 10 s when a warning is active, with alarms always published immediately. The figures exclude TCP/IP and TLS overhead, which add to the real volume.

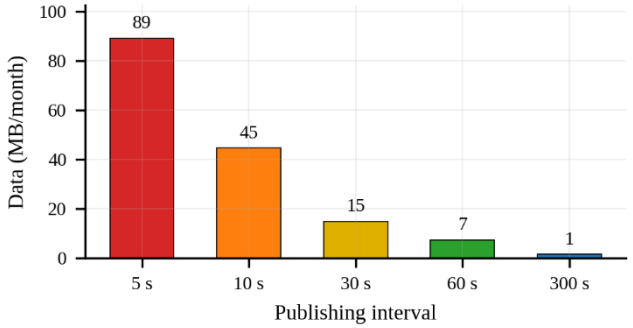


Fig. 8. Estimated monthly data volume versus publishing interval (message payload 149 bytes plus MQTT overhead).

E. Limitations

The results come from a simulation, and they should be confirmed on a prototype installed on a real transformer. The thermal model is the simplified exponential form without the short winding time constant, and its parameters are typical values; for a particular transformer they should be taken from its heat-run test report. The load profile is synthetic, the sensors are assumed to be accurate apart from the added noise, and communication delays and outages are not simulated. The 15% load transfer and the 10 min response delay are assumptions and depend on the utility's procedures.

VI. Advantages, Challenges and Future Scope

Advantages. The system gives continuous visibility of loading and temperature, replaces manual dial readings, produces an ageing estimate that supports maintenance and replacement planning, and costs little compared with the transformer. Power-factor and unbalance data help identify feeders for corrective action, and the stored data can be used for load forecasting.

Challenges. Sensor installation in an oil-filled, outdoor, high-voltage environment must meet safety and weatherproofing requirements. Wi-Fi coverage is often poor near rural transformers, so cellular communication is needed, and its recurring cost must be managed through the choice of publishing interval. Cybersecurity is important because a compromised device could send false data or false trip commands. Power for the electronics must be taken from the LV side, and the unit must survive voltage surges and high temperature inside the enclosure.

Future scope. Dissolved-gas sensors, for example for hydrogen, would extend the system to the detection of internal faults. Machine-learning models trained on the collected data could predict load and temperature for the next hours and give earlier warning. Edge computing could be used to perform automatic load transfer, and the data from many transformers could be combined to find the weakest assets in a network. A pilot installation on a real transformer, with comparison of the model to measured heat-run data, is the next step.

VII. Conclusion

This paper presented the design of a low-cost IoT-based smart monitoring system for oil-immersed distribution transformers, built around an ESP32 microcontroller, standard sensors and the MQTT protocol, and with the IEC 60076-7 thermal model implemented on the device. A simulation of a 100 kVA transformer on a hot overload day showed that an IoT alert followed by a 15% load transfer reduced the time above 120 °C by 86% and the equivalent insulation ageing by 40.4%. A residual-based method detected an injected cooling fault 3.5 h after it began. The data volume can be kept at a few megabytes per month by adjusting the publishing interval. These results show that continuous monitoring, combined with a defined response, can extend transformer life and reduce unplanned outages, and they justify construction and field testing of a prototype.

Acknowledgment

The authors thank the Department of Electrical Engineering, [Name of Polytechnic / Institute], for guidance and laboratory support.

REFERENCES

[1] M. Wang, A. J. Vandermaar, and K. D. Srivastava, "Review of condition assessment of power transformers in service," *IEEE Electr. Insul. Mag.*, vol. 18, no. 6, pp. 12–25, Nov./Dec. 2002.

[2] W. H. Tang and Q. H. Wu, *Condition Monitoring and Assessment of Power Transformers Using Computational Intelligence*. London, U.K.: Springer, 2011.

[3] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Gener. Comput. Syst.*, vol. 29, no. 7, pp. 1645–1660, Sep. 2013.

[4] V. C. Gungor *et al.*, "Smart grid technologies: Communication technologies and standards," *IEEE Trans. Ind. Informat.*, vol. 7, no. 4, pp. 529–539, Nov. 2011.

[5] *IEEE Guide for the Interpretation of Gases Generated in Mineral Oil-Immersed Transformers*, IEEE Std C57.104-2019, 2019.

[6] *Power Transformers—Part 7: Loading Guide for Mineral-Oil-Immersed Power Transformers*, IEC Standard 60076-7, 2018.

[7] *IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators*, IEEE Std C57.91-2011, 2012.

[8] D. Susa, M. Lehtonen, and H. Nordman, "Dynamic thermal modelling of power transformers," *IEEE Trans. Power Del.*, vol. 20, no. 1, pp. 197–204, Jan. 2005.

[9] *Power Transformers—Part 2: Temperature Rise for Liquid-Immersed Transformers*, IEC Standard 60076-2, 2011.

[10] *MQTT Version 3.1.1*, OASIS Standard, Oct. 2014. [Online]. Available: https://docs.oasis-open.org/mqtt/mqtt/v3.1.1/

[11] *ESP32 Series Datasheet*, Espressif Systems, Shanghai, China.

[12] *DS18B20 Programmable Resolution 1-Wire Digital Thermometer*, Datasheet, Maxim Integrated, San Jose, CA, USA.

[13] *Outdoor Type Three-Phase Distribution Transformers Up to and Including 2500 kVA, 33 kV—Specification*, IS 1180 (Part 1), Bureau of Indian Standards, New Delhi, India.