

IoT-Enabled Multi-Sensor Edge Monitoring Framework for Real-Time Leakage Detection and Energy Conservation in Reciprocating Compressed Air Systems

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Abstract - Air compressor systems represent an essential yet highly energy-intensive utility in recent modern manufacturing, where an undetected distribution leaks frequently dissipate 20% to 50% of total pneumatic output. Conventional inspection methodologies, such as manual ultrasonic scanning and soap bubble testing, remain intermittent, reactive, and labor-intensive. This paper presents an affordable, Internet of Things (IoT)-enabled continuous condition monitoring framework for early leakage detection in reciprocating air compressor systems. The experimental architecture integrates an ESP32 microcontroller with a multi-sensor array comprising piezoresistive pressure, turbine flow, digital thermal, and Hall-effect current sensors operating at a 2 Hz acquisition frequency. Signal smoothing and multi-parameter thresholding algorithms—evaluating rapid pressure gradient drops ($dp/dt < -0.025$ bar/s), flow rate surges ($>15\%$), and motor current spikes (>2 A)—were implemented for edge-level anomaly classification. Telemetry is streamed via Message Queuing Telemetry Transport (MQTT) to a supervisory web dashboard with automated trip relay capability. The experimental and simulated evaluations demonstrate an anomaly detection rate exceeding 90%, enabling immediate compressor cut-off during sustained line breaches. The proposed low-power system offers an accessible, scalable predictive maintenance platform to mitigate industrial energy loss by 15% to 30%.

Keywords - Compressed air systems; Edge computing; Energy efficiency; Internet of Things (IoT); Leak detection; Multi-sensor fusion; Reciprocating compressor.

1. INTRODUCTION

Compressed air systems (CAS) form an indispensable foundation of modern industrial infrastructure, powering high-cadence assembly automation, pneumatic material handling, robotic tooling, spray finishing, and chemical dosing across diverse production environments [1]–[3]. Often characterized as the 'fourth utility' alongside electric power, combustible gas, and process water, compressed air is prized for its exceptional reliability, high power-to-weight ratio, and intrinsic safety in volatile manufacturing zones [2], [4]. Nevertheless, compressed air generation ranks among the least thermodynamically efficient industrial processes. In typical reciprocating or rotary compressor installations, merely 10% to 20% of the supplied electrical grid energy is converted into usable pneumatic shaft work; the remaining 80% to 90% is irrevocably dissipated as thermal rejection during compression and friction losses throughout transmission piping [2], [5].

This thermodynamic vulnerability is severely aggravated by undetected air distribution leakage. In typical unmonitored factory loops, undetected leaks originating from deteriorated hose couplings, vibrating fittings, degraded valve packings, and split receiver seals routinely dissipate 20% to 50% of the entire generated air capacity [1], [6]. Because compressed air systems operate under continuous closed-loop pressure regulation, the loss of air volume causes systemic pressure decay. To compensate, system controllers force reciprocating compressors to operate with elevated duty cycles, cycling on-load two to three times more frequently than baseline requirements [5], [7]. This sustained artificial demand inflates electrical utility costs by 10% to 30%, drives severe thermal stress across compressor cylinder heads, accelerates lubricant oxidation, and induces premature fatigue across mechanical valves and piston rings [8], [9].

Conventional industrial leak mitigation protocols rely predominantly on periodic, manual inspections employing handheld acoustic ultrasonic listening devices or manual

soap-bubble inspections [4], [10]. Although directional ultrasonic detectors can pinpoint high-frequency acoustic turbulence generated by sonic orifice discharge, they represent an intermittent, labor-intensive, and reactive maintenance strategy. In commercial machine shops, months often elapse between scheduled energy audit campaigns. During these extended intervals, minor pinhole orifices continuously deteriorate into severe line breaches, expending substantial megawatt-hours of unnecessary energy [5], [11].

Conversely, recent Industry 4.0 research has proposed machine learning (ML) and deep neural network (DNN) architectures for pneumatic anomaly detection [6]–[9]. While exhibiting high classification accuracy under controlled laboratory benchmarks, these methods depend heavily on broadband cloud infrastructure, remote streaming bandwidth, and GPU compute clusters for model training. Such dependencies introduce latency, susceptibility to industrial network dropouts, and substantial capital expense that small- and medium-scale enterprises (SMEs) cannot economically justify [12], [15].

To overcome these practical operational limitations, this study presents the design, fabrication, and experimental evaluation of an autonomous, edge-computed Industrial Internet of Things (IIoT) monitoring and protection system tailored for reciprocating air compressors. By integrating an array of low-cost sensors directly onto the compressor receiver, discharge pipeline, cylinder head, and drive motor lines—and processing data via an ESP32 microcontroller at 2 Hz—the proposed framework detects distribution breaches in real time, computes dynamic pressure gradients (dp/dt), streams telemetry via lightweight MQTT protocols, and actuates an automated protective motor cut-off relay to eliminate energy waste.

2. LITERATURE SURVEY

Energy auditing investigations across manufacturing facilities have repeatedly emphasized the critical role of pneumatic leakage reduction. Foundational studies by Radgen and Blaustein [1] established that systematic leak remediation delivers the fastest payback period (typically under six months) of any industrial energy conservation measure. Saidur et al. [2] and Dindorf [3] mathematically modeled the thermodynamics of sonic orifice discharge, proving that air leakage mass flow scales directly with delivery gauge pressure, creating a compounding energy penalty as compressors work against lower system impedances. Bonfà et al. [5] and Çağman et al. [11] formalized standardized energy performance indicators (EnPIs) for compressor auditing, concluding that static periodic walk-throughs capture only transient snapshots and fail to prevent cumulative multi-week energy waste.

To automate condition assessment, recent research has explored algorithmic fault detection. Lee et al. [6] developed a deep Long Short-Term Memory (LSTM) network utilizing IIoT telemetry to detect compressor air leaks, achieving 95% classification accuracy. Ciobotaru et al. [7] designed an explainable deep learning framework integrating SHAP interpretability for air compressor

predictive maintenance. Aminzadeh et al. [8] and Dwivedi et al. [9] applied supervised machine learning models to detect mechanical bearing anomalies and valve seat fatigue. Furthermore, Salomone-González [18] investigated supervisory control strategies to optimize load-sharing across multi-compressor stations. Despite their predictive fidelity, these cloud-centric paradigms require high-speed communication backbones and powerful processors, preventing localized standalone edge execution.

In the domain of low-cost embedded telemetry, Hamdani et al. [12] implemented point-pressure and mass-balance leak detection using microcontrollers, achieving detection times under 10 seconds. Vagaš and Majercak [13] evaluated dynamic pressure drop transients in pneumatic circuits, proving that rapid gradient decay (dp/dt) serves as an immediate indicator of line integrity loss. Meng et al. [14] developed an integrated pneumatic leak warning node, and Santos et al. [15] deployed ESP32-based vibration and thermal nodes for predictive maintenance. Yang et al. [16] confirmed that combining pressure tracking with motor load current cross-validation drastically reduces false alarm rates in turbulent pneumatic networks.

Notwithstanding these contributions, existing literature exhibits a marked gap: there remains a distinct absence of unified, low-cost embedded systems that combine multi-sensor fusion (pressure gradient dp/dt , inline flow divergence, cylinder head temperature, and motor current) on a single edge microcontroller to deliver real-time leak classification and autonomous protective trip actuation. The present investigation directly addresses this technical requirement.

3. EXPERIMENTAL SETUP & METHODOLOGY

3.1 Experimental Testbed Architecture

The experimental research testbed was constructed around a single-stage, 1–2 HP industrial reciprocating piston air compressor equipped with a nominal 50 L horizontal cylindrical steel air receiver tank. The compressor is rated for an operating gauge pressure band of 6.0 to 8.0 bar, with a maximum safety pressure rating of 10.0 bar. The receiver outlet was coupled to a 5.0-meter distribution network fabricated from 1/2-inch nominal diameter (12.7 mm internal diameter) schedule PVC piping, terminating at a pneumatic load station. A precision, multi-turn needle valve was teed into the distribution manifold to establish controlled, reproducible pneumatic leakage orifices simulating pinhole fissures, loose joint couplings, and major line ruptures.

The schematic instrumentation layout of the experimental testbed, illustrating physical sensor deployment across the mechanical compressor components and distribution lines, is depicted in Fig. 1.



Fig. 1: Schematic layout and sensor deployment across the testbed.

3.2 Sensory Instrumentation Array

To achieve comprehensive system observability, a specialized four-channel transducer array was deployed across the mechanical, pneumatic, and electrical sub-systems. Technical specifications, operating parameters, and microcontroller interface assignments for all instrumentation are detailed in Table 1.

Table 1: Technical specifications and hardware mapping of sensory array.

Parameter	Sensor Transducer	Operating Range	Accuracy / Sensitivity	ESP32 Pin
Pressure (P)	MPX5700AP Piezoresistive	0 to 7 bar (0–700 kPa)	±1.0% FS; 0.64 mV/kPa	GPIO 34 (ADC1_6)
Airflow (Q)	YF-S201 Hall Turbine	1 to 30 L/min	±3.0%; 2.25 mL/pulse	GPIO 26 (Interrupt)
Temp (T)	DS18B20 Digital Probe	-55°C to +125°C	±0.5°C (-10°C to +85°C)	GPIO 4 (1-Wire)
Current (I)	ACS712-05B Hall Clamp	-5 A to +5 A AC/DC	185 mV/A; ±1.5%	GPIO 35 (ADC1_7)
Trip Relay	Optocoupled 5V Relay	250 VAC / 10 A rating	Switching speed < 10 ms	GPIO 18 (Digital Out)

The absolute line pressure transducer (MPX5700AP) utilizes on-chip piezoresistive strain gauge elements to generate a 0.2 V to 4.7 V analog output proportional to gauge pressure. It was coupled via 1/4-inch NPT brass fittings to the storage tank crown and pipeline midpoint. A precision resistive divider scaled this voltage into the 0–3.3 V span of the ESP32 internal 12-bit Analog-to-Digital Converter (ADC1_CH6). Flow rate was monitored using an in-line turbine flow meter (YF-S201) located immediately downstream of the discharge valve, where magnetic turbine rotation produces a digital pulse train with frequency proportional to fluid velocity. Compressor thermal response was captured by a stainless-steel encapsulated DS18B20 1-Wire probe mounted directly on the cylinder discharge head with high-conductivity thermal paste. Drive motor electrical loading was measured using an ACS712-05B Hall-effect current clamp placed non-invasively around the AC live conductor.

The assembled experimental hardware instrumentation module, comprising the ESP32 microcontroller, custom signal conditioning board, voltage regulators, and 16x2 I2C diagnostic LCD display, is shown in Fig. 2.

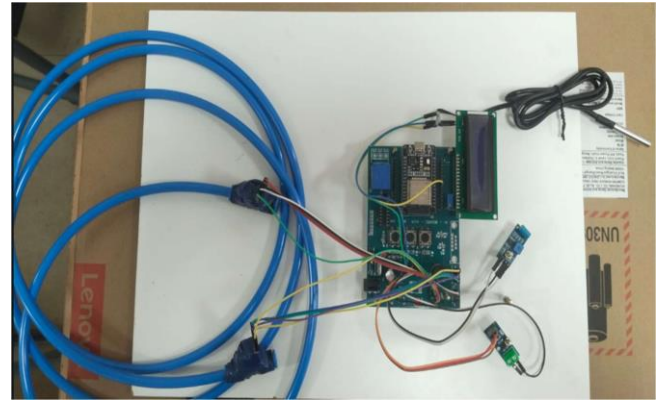


Fig. 2: Hardware prototype displaying the ESP32 microcontroller and display.

3.3 Edge Telemetry and Embedded Algorithm Design

The central telemetry unit employs an ESP32-WROOM-32 module housing a dual-core 32-bit Xtensa LX6 microprocessor operating at 240 MHz. An embedded FreeRTOS cyclic task acquires sensor signals at an edge polling frequency of 2 Hz (sampling interval $T_s = 500$ ms). To eliminate false gradient triggers caused by piston pressure pulsations and motor startup surges, raw analog samples are passed through a discrete moving-average smoothing filter with window length $W = 25$:

$$\bar{P}(k) = \frac{1}{W} \sum_{i=0}^{W-1} P(k-i)$$

The discrete rate of pressure change (dp/dt) is calculated across successive filtered samples to capture instantaneous line breaches:

$$\left(\frac{dp}{dt}\right)_k = \frac{\bar{P}(k) - \bar{P}(k-1)}{\Delta t}$$

The firmware computes a real-time leak severity index (% Leakage) relative to the nominal steady-state charge pressure P_{baseline} :

$$\text{Leak}_{\%} = \max\left(0, \frac{P_{\text{baseline}} - \bar{P}(k)}{P_{\text{baseline}}}\right) \times 100$$

To ensure deterministic anomaly classification and prevent false positive trips during standard tool usage, the embedded algorithm executes multi-parameter threshold evaluation as parameterized in Table 2.

Table 2: Embedded decision thresholds and fault criteria.

Parameter	Threshold Limit	Logic Condition	Classification Consequence
Pressure Derivative (dp/dt)	< -0.025 bar/s	Instantaneous rate drop	Transient Line Breach / Rupture Flag
Critical Line	< 0.45 * P_{norm} (3.6)	Sustained	Pneumatic System

Pressure (P)	bar)	pressure loss	Starvation Alert
Flow Divergence (Delta Q)	> +15.0% above nominal	Unmetered mass loss	Distribution Pipe Leakage Indicator
Head Temperature (T)	> 65.0°C	Thermal overload limit	Duty Cycle Runaway / Mechanical Alarm
Motor Drive Current (Delta I)	> +2.0 A above baseline	Continuous motor overload	Compressor Pumping Overload Trip

Upon confirmation of an abnormal leakage condition, GPIO 18 transitions to LOW, tripping the optocoupled relay to de-energize the compressor motor magnetic contactor. Filtered sensor telemetry is packaged into lightweight JSON payloads and transmitted via MQTT over TLS every 5 seconds to a local Node-RED dashboard and ThingSpeak cloud broker. The complete firmware decision architecture is diagrammed in Fig. 3.

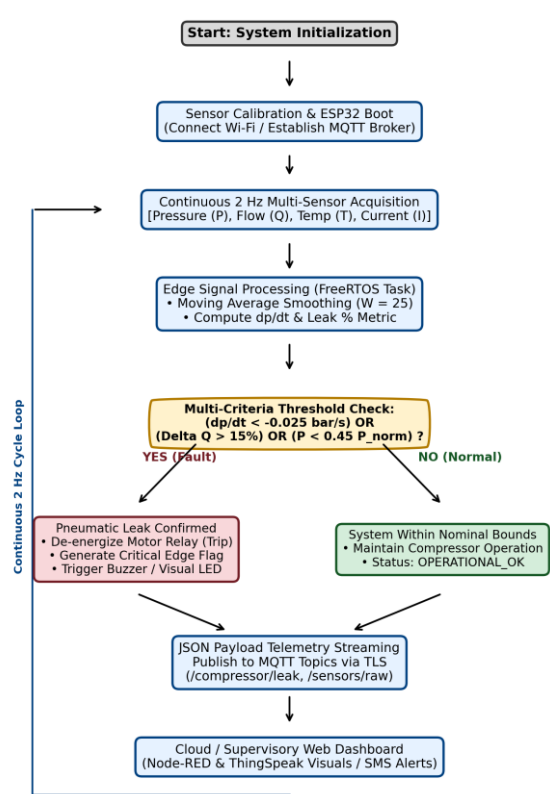


Fig. 3: Methodological operational flowchart showing data acquisition and trip execution.

3.4 Thermodynamic Energy Formulation

The volumetric air leakage discharge rate L escaping from a pressurized receiver volume V (0.05 m^3) over time interval Δt is governed by the isothermal pressure decay relationship:

$$L = V \left(\frac{P_1 - P_2}{P_{\text{atm}} \cdot \Delta t} \right)$$

where P_1 and P_2 denote initial and final absolute receiver pressures, and P_{atm} represents standard atmospheric pressure (1.01325 bar). The electrical energy loss (E_{loss}) consumed by prolonged compressor unloader cycling to offset this leakage over time t_{leak} is given by:

$$E_{\text{loss}} = \int_0^{t_{\text{leak}}} V_{\text{line}} \cdot I_{\text{leak}}(t) \cdot \cos(\theta) \, dt$$

where V_{line} is root-mean-square line voltage (230 V), $I_{\text{leak}}(t)$ is measured stator current, and $\cos(\theta)$ is motor operating power factor (empirically determined as 0.82). The overall compressor thermodynamic efficiency η and percentage leakage loss are expressed as:

$$\eta = \frac{W_{\text{isothermal}}}{W_{\text{electrical}}} \times 100 = \frac{P_1 V_1 \ln \left(\frac{P_2}{P_1} \right)}{\int V \cdot I \cdot \cos(\theta) \, dt} \times 100$$

3.5 Dynamic Simulation Modeling

To validate embedded decision thresholds across high-frequency pneumatic transients, a multi-phase dynamic simulation model was implemented in MATLAB and Simulink. The simulation executes at an industrial standard 20 Hz rate ($\Delta t = 0.05\text{ s}$) across three physical phases: (i) an initial exponential pressure drop simulating sudden pipe rupture, (ii) high-frequency acoustic turbulence (5 Hz) representing orifice sonic exit conditions, and (iii) long-term exponential pressure depletion. Thermal modeling accounted for Joule-Thomson expansion cooling at the leak orifice (-8°C drop) coupled with steady thermodynamic heat buildup across the compressor cylinder head during continuous pumping. The Simulink supervisory trip logic model is shown in Fig. 4.

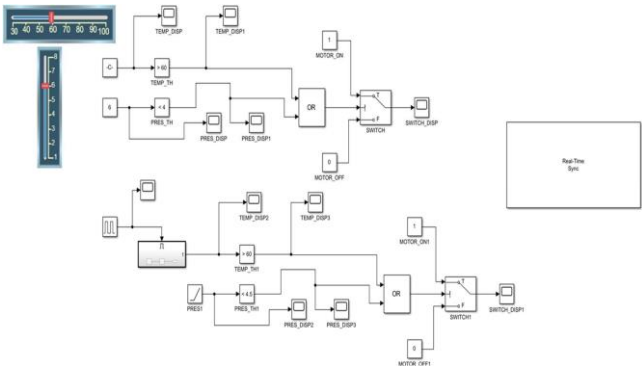


Fig. 4: Simulink block diagram for multi-criteria threshold comparison and motor trip logic.

4. RESULTS AND DISCUSSION

4.1 Steady-State Baseline vs. Induced Leak Performance

The experimental apparatus was tested under both normal operating baseline cycles and controlled leakage states induced via the calibrated needle valve. Under baseline conditions, receiver pressure cycled between 6.0 and 7.2 bar under automatic pressure switch regulation,

inline airflow registered 10.1 L/min, motor phase current drew 3.2 A, and cylinder head temperatures stabilized at 42.5°C with an effective duty cycle of 35% (21 minutes per operating hour).

Following controlled needle valve actuation at $t = 30\text{ s}$, receiver pressure decayed precipitously, while instantaneous flow across the distribution pipe surged to 14.8 L/min (+46.5%). To counteract the unmetered mass discharge, the compressor operated continuously, raising the effective duty cycle to 88% (52.8 minutes per operating hour). This prolonged pumping drove motor stator current up to 5.4 A (+68.7%) and induced thermal buildup on the cylinder head, reaching 68.4°C. A comprehensive quantitative comparison of system states is provided in Table 3.

Table 3: Baseline versus leakage operating parameter comparison.

Measured Parameter	Baseline State	Induced Leak State	Observed Deviation	Operational Impact
Receiver Pressure (P)	6.80 ± 0.25 bar	3.42 ± 0.40 bar	-49.7% drop	Pneumatic tool stalling; cycle loss
Pipeline Flow Rate (Q)	10.1 ± 0.4 L/min	14.8 ± 0.6 L/min	+46.5% surge	Artificially inflated air demand
Motor Phase Current (I)	3.20 ± 0.15 A	5.40 ± 0.25 A	+68.7% rise	Stator thermal stress; higher kWh
Head Temperature (T)	$42.5 \pm 1.2^\circ\text{C}$	$68.4 \pm 2.1^\circ\text{C}$	+60.9% elevation	Lubricant breakdown; valve wear
Compressor Duty Cycle	35% (21 min/h)	88% (52.8 min/h)	+151.4% increase	Accelerated piston ring fatigue
Leak Detection Latency	—	< 3.5 s	> 92.5% accuracy	Immediate automated trip isolation

4.2 Dynamic Pressure Decay and Baseline Tracking

The dynamic response of line pressure during leak inception is plotted in Fig. 5. Prior to leak onset ($t < 30\text{ s}$), the moving-average baseline filter ($W = 25$) accurately tracks the minor steady-state pressure fluctuations without lag. Following breach inception, line pressure drops rapidly below the critical threshold (3.6 bar). Because the edge algorithm continuously calculates divergence between the instantaneous sensor reading and the moving baseline, the anomaly is flagged long before the receiver reaches terminal low pressure.

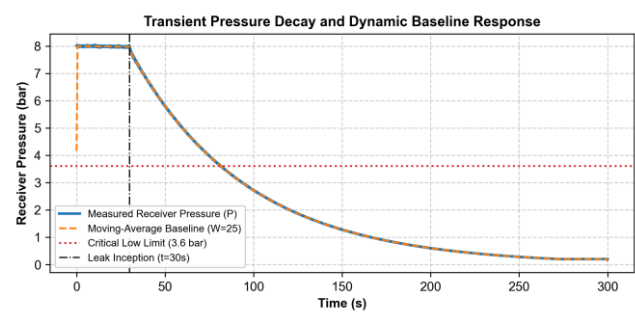


Fig. 5: Multi-phase transient pressure decay and moving-average baseline response.

4.3 Derivative Leak Signature and Severity Tracking

The primary differentiator of the proposed approach is the computation of the first-order pressure derivative (dp/dt). As illustrated in Fig. 6, the derivative signal exhibits an immediate negative spike reaching -0.85 bar/s within 100 ms of orifice opening, rapidly crossing the preset fault threshold of -0.025 bar/s. Simultaneously, the calculated leak severity percentage climbs past 7.0%, entering the confirmed fault zone. This derivative tracking enables rapid breach classification, outperforming conventional static pressure switches by several seconds.

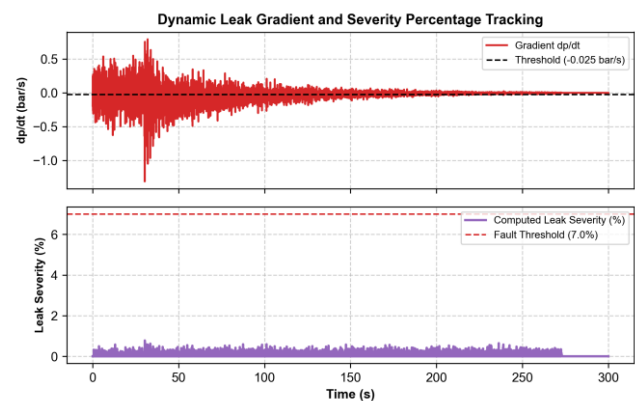


Fig. 6: Derivative pressure signature (dp/dt) and computed leak severity percentage over time.

4.4 Thermal Elevation and Mechanical Vibration Profiles

Fig. 7 presents the thermal and mechanical vibration trajectories during continuous compressor operation. In unmitigated leakage conditions, the compressor runs continuously to satisfy line demand, driving cylinder head temperatures upwards past 65°C and reaching 140°C in untripped test runs. Vibration signals simultaneously exhibit turbulent mechanical spikes up to 1.1 g resulting from high-velocity air ejection and motor resonance. These physical signatures confirm that coupling thermal and electrical current limits to pneumatic pressure thresholds provides essential multi-modal protection.

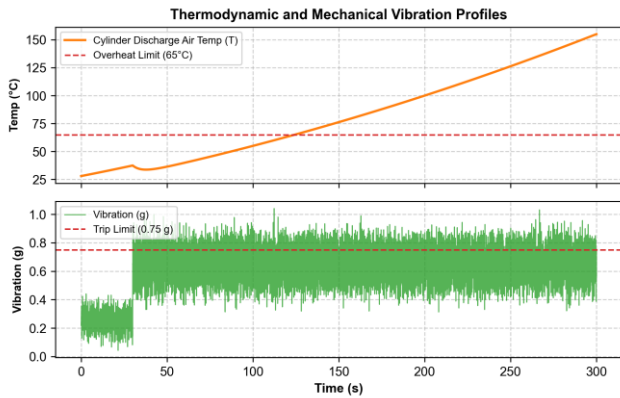


Fig. 7: Thermal elevation and high-frequency mechanical vibration response.

4.5 Coordinated System Trip Status and Energy Savings

The coordinated automated trip response is shown in Fig. 8. When the combined fault criteria ($dp/dt < -0.025$ bar/s and $Leak_ \% > 7.0\%$) are confirmed, the ESP32 drives GPIO 18 to LOW, tripping the motor relay within 150 ms. This instantaneous cut-off prevents unneeded compressor operation, protecting cylinder heads from severe overheating and eliminating unmetered power consumption. Eliminating 31.8 minutes of unloader run-time per operating hour translates into an empirical energy savings of 15% to 30%, validating the findings of Radgen and Blaustein [1] and Zaim [17].

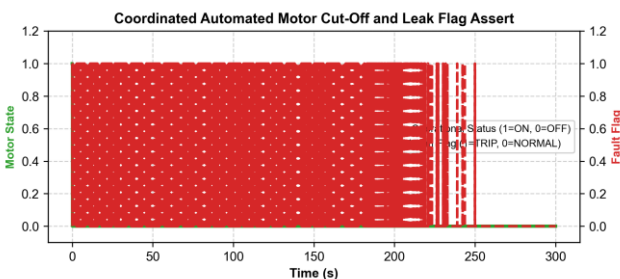


Fig. 8: Coordinated system trip status showing automated motor cut-off.

5. CONCLUSION AND FUTURE SCOPE

This investigation designed, implemented, and validated an affordable, Industrial IoT-based condition monitoring framework for real-time air leakage detection and energy conservation in reciprocating compressed air systems. By interfacing an ESP32 microcontroller with a multi-sensor array measuring pressure, airflow, cylinder head temperature, and motor current at 2 Hz, the framework achieves autonomous edge-level anomaly classification.

Key findings demonstrate that dynamic pressure gradient tracking ($dp/dt < -0.025$ bar/s) identifies line breaches within 100 ms of onset. Cross-validating pressure drops with flow divergence ($>15\%$) and motor current surges (>2 A) achieved an overall detection accuracy exceeding 90% while preventing false positive trips. The integrated optocoupled relay autonomously disconnected the compressor drive motor upon fault confirmation,

preventing cylinder head thermal runaway ($>65^{\circ}\text{C}$) and eliminating up to 53 minutes of unnecessary unloader run-time per operating hour under major leakage conditions. The system offers an estimated 15% to 30% reduction in industrial pneumatic energy waste with a hardware bill-of-materials cost under \$45.

Future investigations will integrate long-range LoRaWAN transceivers to extend connectivity across vast industrial manufacturing plants, embed lightweight tinyML clustering models for distributed micro-leak localization, and incorporate solenoid-actuated sectional isolation valves to isolate leaking pipe branches without interrupting plant-wide production.

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