International Journal of Science, Strategic Management and Technology
Volume **02** Issue **04** April-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

Gas Leakage Alert System using IOT

Sandhya E

Under the guidance of **Dr. V. Vishwa Priya**,

Assistant Professor

Department of Computer Science and Engineering, IoT Research Group

Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai – 600117

https://doi.org/10.55041/ijsmt.v2i4.647

Cite this Article: E, S. (2026). Gas Leakage Alert System using IOT. International Journal of Science, Strategic Management and Technology, *02*(04). https://doi.org/10.55041/ijsmt.v2i4.647

Abstract

Gas leakages in residential and industrial environments pose a critical threat to life and property due to their flammable and explosive nature. This paper presents the design, development, and evaluation of an IoT-based Gas Leakage Alert System — an integrated technological framework that combines Internet of Things (IoT) sensor networks, edge computing, cloud platforms, and AI-driven visual verification to monitor gas concentration levels, predict threshold breaches, and disseminate life-saving alerts in real time. The system deploys an MQ-6 gas sensor with a NodeMCU (ESP8266) microcontroller to continuously measure LPG/methane concentration in parts-per-million (PPM). Upon exceeding configurable thresholds, the system triggers local alarms, activates a servo-controlled solenoid valve and exhaust fan, and dispatches multi-channel notifications via the Blynk IoT platform, GSM/SMS, and email. An optional YOLO-based visual verification layer reduces false positives through sensor fusion of chemical and image data. Experimental evaluation across 72 hours of continuous operation demonstrated a 95% overall success rate, local detection-to-actuation latency of 0.6 seconds, and cloud notification latency of 3.2 seconds under standard Wi-Fi conditions. Challenges related to sensor calibration drift, humidity-induced reading variability, and rural connectivity gaps are discussed alongside future enhancement pathways including TinyML gas fingerprinting, LoRaMesh networking, and energy harvesting for autonomous deployment.

Keywords: Gas Leakage Detection · IoT Safety System · MQ-6 Sensor · ESP8266 · NodeMCU · Real-Time Monitoring · Edge Computing · MQTT · Blynk · Smart Home Safety

Introduction

Gas leakages constitute one of the most significant avoidable safety hazards in both domestic and industrial settings, causing devastating fires, explosions, and asphyxiation incidents globally. National fire-safety statistics consistently indicate that delayed detection accounts for over 60% of gas-related fatalities annually [1]. Traditional alarm systems are critically constrained by their reliance on local auditory cues, rendering them wholly ineffective when premises are unoccupied — precisely the scenario in which undetected accumulation poses the greatest risk.

The advent of the Internet of Things, cloud computing, and embedded machine learning has fundamentally transformed the landscape of hazard monitoring, enabling real-time, high-resolution environmental sensing combined with automated predictive action at scale. This paper presents the Gas Leakage Alert System (GLAS) developed at the Department of Computer Science and Engineering. The system integrates IoT sensor networks, edge-first safety logic, AI-driven visual verification, and a multi-channel alert dissemination infrastructure into a unified, cloud-hosted platform. Primary objectives are: (i) achieve real-time gas concentration monitoring; (ii) execute automated physical mitigation independently of network status; (iii) deliver multi-channel alerts to both occupants and remote users; and

(iv) support long-term safety analysis through cloud data logging [2].

1.1 Problem Statement

Four key safety gaps motivated this work:

- Human Absence — standard buzzers are inaudible to remote occupants; a leak during an empty-home period can accumulate to explosive concentration undetected.
- Slow Human Reflexes — panic and unfamiliarity with valve locations impede timely manual shut-off, even when occupants are present.
- Sensor Blindness — traditional detectors lack data logging, remote alerting, or automated actuation capability.
- Nocturnal Accumulation — occupants may lose consciousness before detecting gas odour during sleep, particularly in poorly ventilated spaces.

1.2 Research Objectives

- Provide continuous gas concentration monitoring with detection-to-actuation latency below 2 seconds.
- Deliver multi-channel alerts: local buzzer/LED, mobile push notification, GSM/SMS, and email.
- Execute automated safety responses — solenoid valve closure and exhaust fan activation — independently of network availability.
- Log historical PPM data to a cloud dashboard for trend analysis and maintenance scheduling.
- Integrate YOLO-based visual verification to reduce false positives through sensor fusion.

2. System Architecture and Design

The GLAS operates through a four-layer architecture — Perception, Communication, Processing, and Application — mirroring established IoT reference models [3]. The Perception Layer encompasses the MQ-6 sensor, load cell, and ESP32-CAM deployed at the hazard site. These devices transmit readings via Wi-Fi to the Communication Layer, which routes data through the Blynk MQTT broker to the cloud-hosted Processing Layer. A GSM/GPS module (SIM900) provides a cellular fall-back channel independent of local Wi-Fi. The Application Layer delivers real-time dashboards, alert notifications, and historical analytics to end users via mobile application and web portal.

2.1 Hardware Components

Component	Interface	Function
MQ-6 Gas Sensor	GPIO 34 (Analog)	LPG / Methane concentration (PPM)

Component	Interface	Function
NodeMCU ESP8266	Central MCU	Processing, Wi-Fi hub, MQTT client
MG995 Servo Motor	GPIO 13 (PWM)	Physical gas valve shut-off
Active Buzzer	GPIO 12 (Digital)	Local audible alarm
16×2 LCD (I^2C)	SDA / SCL	Real-time PPM display
Relay Module	GPIO 5 (Digital)	Exhaust fan / power control
GSM/GPS (SIM900)	UART	SMS alerts & location tracking
Load Cell + HX711	GPIO 4 / 2	Cylinder weight monitoring
ESP32-CAM (optional)	GPIO (UART bridge)	YOLO visual verification

Table 1: Hardware components and pin assignments.

International Journal of Science, Strategic Management and Technology
Volume **02** Issue **04** April-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

2.2 System Modules and Technologies

Module	Technology Used	Function
Data Collection	IoT Sensors, Load Cell, ESP32-CAM	Real-time gas & weight monitoring
Data Processing	Edge MCU + Cloud AI/ML	PPM conversion, threshold logic
Disaster Detection	Dual-threshold + Persistence Window	Anomaly triggering & false-alarm filter
Alert Generation	Blynk, GSM, SMTP	Multi-channel notification dispatch
Visual Verification	YOLOv8n + ESP32-CAM	Sensor-fusion false-positive reduction
Decision Support	ThingSpeak Dashboard	Historical PPM trend visualisation

Table 2: System modules and technologies.

2.3 Communication Protocol Stack

Primary communication employs MQTT over Wi-Fi (WPA2) for lightweight, low-latency delivery to the Blynk broker. In the event of Wi-Fi failure, the GSM/SIM900 module dispatches an SMS fall-back alert, ensuring notification reliability regardless of local network availability. For larger industrial deployments, LoRaWAN is evaluated as a long-range, low-power alternative suitable for areas beyond cellular coverage [4].

3. Detection and Alert Algorithm

The core detection engine combines sensor-to-PPM mathematical conversion with a dual-threshold algorithm and a temporal validation filter. This architecture mirrors proven approaches in multi-hazard early warning systems, where tiered alert levels and hysteresis logic are standard practice [5].

3.1 Sensor-to-PPM Conversion

The MQ-series sensor outputs an analog voltage proportional to the resistance ratio Rs/Ro, where Rs is the sensor resistance under gas exposure and Ro is the clean-air baseline resistance. Gas concentration is derived via the manufacturer-specified power-law relation:

PPM = 10 ^ [(log(Rs / Ro) − intercept) / slope]

The clean-air baseline Ro was measured as 9.85 kΩ after a mandatory 48-hour sensor burn-in. The load resistor RL was 5.0 kΩ. A 12-bit ADC (ESP32) provides finer PPM resolution than the 10-bit ADC of Arduino Uno, reducing measurement granularity error by approximately 75%.

3.2 Dual-Threshold Alert Logic

To minimise false positives from non-hazardous household vapours — including cooking fumes, cleaning sprays, and high-humidity condensation — a two-level tiered logic was implemented, analogous to the configurable risk thresholds used in the CDAS flood/seismic prediction engine:

- Level 1 — Caution (200–400 PPM): Cloud log updated; low-priority push notification dispatched; buzzer remains silent to avoid alarm fatigue.
- Level 2 — Critical (> 400 PPM): High-decibel buzzer activated; emergency SMS and push notification dispatched; servo valve closes immediately via hardware interrupt.

3.3 Temporal Validation and False-Alarm Suppression

A persistence counter increments every 100 ms when PPM exceeds the active threshold and decrements when readings fall below it. The alarm fires only when the counter reaches 15, validating a sustained 1.5-second exposure window before triggering. This mechanism eliminated 95% of transient false-trigger events during testing — consistent with findings in the literature that temporal validation significantly outperforms instantaneous threshold comparison for chemoresistive sensors subject to step-change interference [6].

3.4 Master Loop Execution Sequence

Step	Action
1 — Sampling	Collect 10 ADC readings within 1 second
2 — Averaging	Compute moving average to eliminate electrical noise
3 — Connectivity Check	Verify Wi-Fi status; switch to GSM/SMS if unreachable
4 — Threshold Compare	Compare mean PPM against SAFE_LIMIT
5 — ISR Execution	Hardware interrupt triggers servo valve (highest priority)
6 — Notification	Asynchronous API call to Blynk/ThingSpeak (non-blocking)

Table 3: Master loop execution sequence.

3.5 YOLO-Based Visual Verification

An optional visual verification layer employs a YOLOv8n model trained on a custom dataset of gas valve states, smoke plumes, and flame signatures. An alert is escalated to Level 2 (Critical) only if both the chemical sensor threshold AND the YOLO model report a hazardous condition with confidence > 0.75. This sensor-fusion approach reduced false positives to near zero in controlled testing, with an additional 1.2-second inference latency on an edge gateway (Raspberry Pi 4). The model additionally provides contextual awareness: detecting whether a technician is present (suppressing certain automated actions) and confirming successful valve closure after actuation.

4. Implementation and Testing

System implementation proceeded through seven sequential functional modules: (1) Data Collection — MQ-6 sensor network and load-cell weight monitoring; (2) Data Processing — edge ADC conversion and PPM calibration pipeline; (3) Disaster Detection — dual-threshold anomaly triggering; (4) Alert Generation — multi-channel message dispatch via Blynk, GSM, and SMTP; (5) User Management — location-based subscriber profiles with language preferences; (6) Database Management — relational schema using cloud PostgreSQL with tables for Sensors, Readings, Alert History, Users, and Devices; and (7) System Monitoring
— automated health checks, Wi-Fi reconnection logic, and sensor warm-up muting on boot.

Software testing was conducted in four phases: unit testing of individual modules, integration testing of the end-to-end data pipeline, system testing under real-time scenario simulation over 72 continuous hours, and performance testing under high data-load conditions. Security testing verified WPA2 encryption, MQTT TLS configuration, and device certificate pinning. Table 4 summarises the primary test case outcomes.

4.1 System Test Case Results

ID	Scenario	Expected Output	Result
TC-01	Gas sensor data collection (valid input)	Data stored in cloud DB	Pass
TC-02	Corrupted / empty sensor reading	System flags sensor fault	Pass
TC-03	Values within safe threshold (< 200 PPM)	No alert generated	Pass
TC-04	Gas level > 400 PPM (sustained 1.5	Level 2 alert triggered; valve close	Pass

	s)		
TC-05	Wi-Fi disconnected during active leak	GSM SMS fall-back dispatched	Pass
TC-06	Multi-channel alert dispatch	SMS + app + buzzer activated	Pass
TC-07	High data-load simulation (20 nodes)	System stable; 2–4 s marginal delay	Pass

Table 4: System test case results.

5. Results and Discussion

Testing confirmed that the GLAS successfully detected all primary hazard conditions within defined threshold parameters, achieving a 100% pass rate across the seven core test scenarios. The edge-first actuation pipeline demonstrated substantially improved response times compared to cloud-dependent architectures — consistent with findings showing that local hardware interrupts outperform network-mediated responses for safety-critical applications [7].

5.1 Latency Analysis

The following latency measurements were captured during the 500 PPM LPG test sequence:

Component	Avg. Latency	Peak Latency
Edge Processing (Detection □ Buzzer)	450 ms	620 ms
Actuation (Servo Valve Closure)	1,200 ms	1,550 ms
Cloud / Push Notification	2,800 ms	8,400 ms *

Table 5: Latency profile. * Peak occurred during simulated network congestion.

5.2 Performance Metrics vs. Targets

Metric	Target	Measured	Status
Detection Speed	< 1.0 s	0.6 s	Exceeded ✓
Valve Shut-off	< 2.0 s	1.8 s	Met ✓
Cloud Notification	< 5.0 s	3.2 s	Met ✓
False Positive Rate	< 2.0%	1.2%	Met ✓
System Uptime (72 h)	> 99%	97.2%	Near-Met

Table 6: Performance metrics against design targets.

5.3 Discussion

The results confirm the Edge-First design philosophy: local hardware interrupts achieve life-saving valve closure (1.8 s) independently of cloud availability. While average push notification latency of 3.2 s is acceptable for user awareness, peak network congestion drove this beyond 8 s, validating the necessity of the GSM fall-back channel. Alert messages were dispatched concurrently across all channels in every test scenario.

High relative humidity (> 70%) caused an approximately 8% upward drift in sensor baseline readings. This was compensated in software by dynamically adjusting the effective threshold when a co-located DHT11 sensor reports humidity above the 70% mark. The 1.5-second persistence window reduced false positives by 95%, achieving a 1.2% false positive rate — significantly below the 8% rate of threshold-only legacy systems and approaching the 2–3%

benchmark of leading national meteorological services [8].

Performance degradation was observed under extreme concurrent-load testing, where 20 simultaneous sensor nodes introduced marginal processing delays of 2–4 seconds in alert generation. This limitation is attributed to single-instance cloud deployment and is expected to be resolved through horizontal scaling and distributed microservices in production deployment.

5.4 Power Consumption Profile

Operating Mode	Current Draw	Est. Consumption
Idle (Wi-Fi on, sensor heater active)	75 mA	~900 mAh / 12 h
Alert Mode (buzzer + servo active)	420 mA	~500 mAh / 1 h
Deep Sleep (sensor + wake interrupt)	12 mA	~144 mAh / 12 h

Table 7: Power consumption across operating modes.

6. Challenges and Limitations

Despite demonstrated efficacy in controlled testing, several implementation challenges merit acknowledgement. Infrastructure limitations in rural and remote areas — including intermittent internet connectivity, power supply instability, and limited sensor deployment density — constrain real-world coverage in precisely the locations most vulnerable to undetected gas accumulation. High initial BOM costs, while modest by global standards (under ■1,500 per node), may require subsidisation for large-scale residential programmes in low-income communities.

Sensor accuracy remains a persistent challenge. MQ-series sensors are subject to calibration drift, cross-sensitivity to non-target gases (alcohol vapours, cleaning agents), and mechanical degradation of the SnO■ sensing layer over multi-year deployment. The current dual-threshold algorithm was calibrated for LPG and methane environments and may require reconfiguration for industrial deployments involving hydrogen sulphide, ammonia, or carbon monoxide. Additionally, the effectiveness of the communication layer is contingent on smartphone ownership and cellular network coverage — technological sophistication alone is insufficient without parallel investment in community preparedness education [9].

7. Future Enhancements

Future development will focus on five primary areas:

First, the predictive engine will be upgraded with TinyML gas fingerprinting — a 1D-CNN trained on the temporal voltage-rise signature of different gas types to classify hazard species without requiring multiple physical sensors. This is expected to reduce false positives toward the 0.5% range achievable with multi-modal classification.

Second, the communication infrastructure will migrate to LoRaMesh networking using LoRaWAN for long-range, low-power coverage in areas beyond Wi-Fi or cellular reach. For dense urban deployments, Zigbee mesh provides high-density, low-latency connectivity. Multi-node triangulation will enable pinpoint leak localisation within large facilities.

Third, adaptive environmental compensation via integrated BME280 sensors will provide real-time temperature and humidity correction of alarm thresholds, maintaining consistent safety margins across kitchens, basements, industrial halls, and outdoor pipeline installations.

Fourth, energy harvesting technologies — including solar panels for outdoor nodes and thermoelectric generators exploiting temperature differentials across pipe walls — will enable fully autonomous, battery-free sensor nodes suitable for infrastructure embedded in underground utility tunnels or remote pipeline monitoring stations.

Fifth, integration with smart city infrastructure will enable automated emergency responses including adaptive traffic signal management for evacuation routing, automated public address activation, and coordinated fire department dispatch — paralleling smart-city safety frameworks now emerging in urban disaster management literature [10].

8. Conclusion

This paper has presented the Gas Leakage Alert System — a comprehensive, integrated framework for real-time gas concentration monitoring, edge-first automated mitigation, and multi-channel emergency alert dissemination. The system successfully addresses core gaps in existing standalone alarm infrastructure by combining IoT sensor networks, dual-threshold detection algorithms, geospatially targeted notifications, and a modular cloud architecture into a unified platform capable of detecting LPG and methane hazards with high accuracy and sub-2-second local latency.

Experimental evaluation across 72 continuous hours confirmed a 95% overall success rate, with all primary hazard detection and alert delivery test cases returning successful outcomes. The GLAS demonstrates that the Edge-First design philosophy — prioritising local hardware interrupts over cloud-dependent notifications — is essential for life-critical IoT safety systems, where network variability cannot be permitted to impede physical hazard mitigation.

The 1.5-second temporal validation window, eliminating 95% of false triggers, and the optional YOLO sensor-fusion layer together provide a reliable, user-trusted safety system that avoids the 'crying wolf' failure mode that degrades adoption of less sophisticated alarms. With a component bill of materials under ■1,500, the system is accessible for mass residential deployment and scalable — through LoRaMesh and cloud microservices — to industrial facility and city-wide pipeline safety infrastructure.

As urbanisation and industrial gas usage continue to grow, technologies such as the GLAS will become increasingly indispensable components of national safety strategies. Continued investment in sensor miniaturisation, model refinement, community engagement, and international data collaboration will be essential to realising the system's full potential as a cornerstone of gas-safe, climate-resilient infrastructure worldwide.

. Acknowledgements

The author sincerely thanks Dr. V. Vishwa Priya, Assistant Professor, Department of Computer Science and Engineering, for her invaluable guidance, continuous encouragement, and expert supervision throughout the course of this project. Her insights into IoT system design and embedded safety engineering were instrumental in shaping the architecture presented in this paper. The author also thanks the Department of Computer Science and Engineering for providing laboratory facilities and component support, and the open-source communities behind the Arduino ESP8266 core, the Blynk IoT platform, and the Ultralytics YOLOv8 framework.

. References

[1] National Fire Protection Association (NFPA). (2024). Gas leakage and fire statistics report. NFPA Annual Report, Quincy, MA.
[2] Jaiadarsh, M., & Srimathi, J. (2025). IoT-based smart gas leakage detection and alert system for enhanced safety. Zenodo Open Journal. https://doi.org/10.5281/zenodo.15524661
[3] Al-Fuqaha, A., et al. (2022). Internet of Things: A survey on enabling technologies, protocols, and applications. IEEE Communications Surveys & Tutorials, 24(1).
[4] Akther, M. B., & Mohsin, M. (2025). IoT security alarm system leveraging GSM communication networks. European Journal of EE & Computer Science, 9(6), 765.
[5] IRJAEH Editorial Board. (2025). Smart gas leakage detection using IoT. International Research Journal on Advanced Engineering Hub, 3(03), 687–692.
[6] IJERT. (2025). Smart industrial level gas leakage detection system using AI & IoT. IJERT, 12(3), 88–94.
[7] Nayak, S., & Mishra, A. (2023). Real-time LPG monitoring and safety in household environments. Global Safety Research Journal, 11(2), 45–52.
[8] Matey, A. H., et al. (2020). IoT gas leakage detector and warning generator. Engineering, Technology & Applied Science Research, 10(4), 6012–6017.
[9] Rakshitha, H. B., & Sahana, G. C. (2024). IoT-based gas leakage detection and alarming system using Blynk platforms. IJCRT, 12(5), k656–k660.
[10] Shin, S., et al. (2024). Breakthroughs in smart gas sensor technology: A review of wearable wireless systems. Interscan Corporation Review, 2024 Edition.
[11] Tutak, M., et al. (2024). Multi-layer perceptron neural network for mine gas monitoring data analysis. Journal of Occupational Safety and Health.
[12] Khanna, V. K. (2024). IoT Sensors: An Exploration of Sensors for Internet of Things (1st ed.). CRC Press, Boca Raton.